THE ECONOMICS OF INTERNET PEERING INTERCONNECTIONS

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THE ECONOMICS OF INTERNET PEERING INTERCONNECTIONS

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To my parents, my wife Fatima and son Mustafa

for their patience and encouragement

and

To Dr. Sir Muhammad Iqbal (1877 - 1938)

whose writings on philosophy, metaphysics and mystical poetry

uplifted the spirit when all progress stalled

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SUMMARY

The Internet is composed of thousands of Autonomous Systems (ASes) which interconnect with one another to form the "Internet Ecosystem". The ASes interconnect with one another through two types of links: (a) transit (customer-provider) and (b) peering links. Unlike transit links, peering links are optional for all ASes (except for *Tier-1* ASes which form a clique of peering links) in the context of global reachability. Despite being optional, a rich and dynamic peering fabric exists among ASes in the Internet ecosystem as shown by various studies. Moreover, the importance of peering has grown as one of the main instruments for catching up with asymmetric traffic due to CDNs, online video traffic, performance requirements, etc. However, despite its widespread adoption, peering has been considered a "black art" which is understood in depth by a small community of peering coordinators only. Despite the interest and the intense debate around it, many fundamental questions about peering remain elusive.

The objective of this thesis is to study peering from an economics perspective. The topics explored in this thesis can be divided into the following categories:

1. Fundamental nature of peering among ASes, e.g., what are the main sources of complexity in Internet peering that defy the development of a methodical approach to assess peering relationships? Is peering in the interdomain network a zero-sum game?

2. The current state of the peering ecosystem, e.g., which categories of ASes are more inclined towards peering? What are the most popular peering strategies among ASes in the Internet?

3. The economics of contemporary peering practices, e.g., what is the impact of using

different peering traffic ratios as a strategy to choose peers? Is the general notion that peering saves costs, always valid?

4. Proposition of new peering strategies and their economic comparison with contemporary practices.

We have used analytical game-theoretic modeling, large-scale computational agent-based modeling, and analysis of publicly available peering data to answer the above questions. The main contributions of this thesis include:

Complexities in Internet Interdomain Peering What are the main sources of complexity in identifying potential peers, negotiating a stable peering relationship, and utility optimization through peering? How do contemporary operational practices approach these problems? In this work we address these questions for Tier-2 Network Service Providers. We identify and explore three major sources of complexity in peering: (a) inability to predict traffic flows prior to link formation (b) inability to predict economic utility owing to a complex transit and peering pricing structure (c) computational infeasibility of identifying the optimal set of peers because of the network structure. We show that framing optimal peer selection as a formal optimization problem and solving it is rendered infeasible by the nature of these problems. Our results for traffic complexity show that 15% Network Service Providers (NSPs) lose some fraction of customer traffic after peering. Additionally, our results for economic complexity show that 15% NSPs lose utility after peering, approximately, 50% NSPs end up with higher cumulative costs with peering than transit only, and only 10% NSPs get paid-peering customers.

Computational Agent-based Model of Internet Interdomain Network Formation, Traffic Flow and Economics: As part of the dissertation thesis, we have created GENESIS - an open-source computational agent-based model of interdomain network formation, traffic flow and economics. GENESIS provides us with an elaborate computational testbed through which we can experiment with different interconnection and economic strategies, evaluate them under realistic conditions, and observe how the actions of individual ASes manifest into large-scale behaviors at the macroscopic level.

Data Analysis of the Peering Ecosystem: We carried out data analysis of a publicly available dataset. We mined one of the few sources of public data available about the interdomain peering ecosystem: PeeringDB. We analyzed correlations between different AS characteristics and explored the evolutionary trends of the peering ecosystem, including geographic expansion of players, increase and decrease in traffic volume of different players, and shifts toward more restrictive peering.

A Plausible Explanation for Gravitation of Internet Transit Providers Towards Open Peering: Transit providers are a specific class of networks in the Internet whose business is to transport traffic from the source to destination. Transit providers prefer to be paid for this service instead of doing it for free. Recently, however, a large percentage of transit providers has been offering free peering service to many other ASes. Simultaneously, transit providers, in general, have reported significant reductions in their profits. Using some analytical modeling and large-scale simulations with GENESIS, we explained this counterintuitive phenomenon to be grounded in myopic and selfish decision making of a few ASes in the Internet. We showed that peering decisions in the Internet are not isolated locally, but can have non-local network effects. These non-local effects can force other ASes in the network to follow suit, resulting in a population-wide reduction in profitability.

Proposition of New Practical Peering Strategies: The complexity of the Internet has forced ASes to adopt simple rules-of-thumb as their peering strategies. Sophisticated peering strategies have been considered intractable so far. However, our analysis showed that certain properties of the Internet network structure could be exploited to carry out much more sophisticated peering strategies in a tractable manner. In this research I have proposed sophisticated peering strategies that can be deployed by ASes in practice.

CHAPTER I

INTRODUCTION

The Internet interdomain network is a complex network of approximately 50,000 Autonomous Systems (ASes) which interconnect with one another through transit (customer-provider) or peering links. Peering links fall in one of two categories: (a) settlement-free and (b) paid. A recent study showed the presence of a rich peering fabric at a major European IXP, with more than 67% of all possible links formed between 400 member ASes exchanging more than 10 PB of data on a daily basis [19]. Thus, peering can affect network performance and reachability of millions of Internet users. In the context of interdomain connectivity, ASes face an important question: which other ASes should they peer with?

Internet interdomain peering has been in the spot light in one way or the other for the last two decades because of peering conflicts between different Autonomous Systems (ASes) in the Internet interdomain network. The importance of these issues can be judged from the fact that such disputes have increasingly hit the headlines recently, e.g., the Comcast vs. Level-3 peering dispute [94]. Such disputes have led to litigation, calls for intervention by regulators [69] and legislation at the highest levels of government [89]. These disputes have sometimes resulted in the partitioning of the Internet rendering significant organizations with critical communication needs, e.g., NASA and Federal Aviation Administration (USA), disconnected from the Internet [103]. Furthermore, the frequency of such disputes is likely to increase in future [96].

These peering disputes fueled an intense public debate around peering [87]. The debate touched upon nearly all aspects of network interconnections including pricing, traffic ratios, costs, performance, network neutrality, the power of access ISPs, regulation, etc. However many fundamental questions are still unanswered. In this thesis we explore the entire spectrum of Internet interdomain peering from an economic perspective and explore questions such as: What makes peering so complex that it is understood by a small community of peering coordinators only? What are the main sources of complexity in peering that force the majority of the peering community to resort to simple rules-of-thumb for link formation? Why has peering defied the development of a methodical quantitative approach? Is the general notion that peering saves costs, always valid? Which peering strategies are adopted by different types of ASes? Can we explain the counterintuitive phenomenon of a significant fraction of transit providers adopting Open peering? Furthermore, we propose new practical techniques and strategies for peering that, if deployed, could yield better economic utilities.

1.1 Background

Tens of thousands of Autonomous Systems (ASes) interconnect in a complex and dynamic manner to form the Internet. Each AS is an independent entity under single administrative control, and is identified through a unique AS number (ASN), which is assigned by a central authority, the Internet Assigned Numbers Authority (IANA) [15]. Each AS manages its own internal network topology and traffic routing (intradomain activity) and connects to the rest of the world by forming links with other geographically co-located ASes (interdomain activity). These ASes generate traffic destined for other ASes in the Internet, consume traffic destined for them, and some of them transit traffic, i.e., they carry traffic on behalf of other ASes to transport it to its destination.

ASes belong to different categories: enterprise networks (or stubs), e.g., university campuses, banks etc.; content sources, which generate much more traffic than they consume, e.g., Google, Facebook, YouTube etc.; access providers, which consume much more traffic than they generate, e.g., residential ISPs, Comcast, France Telecom; transit providers, which carry traffic on behalf of other ASes to its destination, e.g., Level 3 Communications, Cogent etc. Various combinations of the aforementioned categories also exist, e.g., ASes that provide both transit and access services such as AT&T. Thus, the Internet is a network of ASes where traffic flows from one AS to another en route to its destination. A traffic flow may traverse multiple transit providers before reaching its destination AS. Additionally, ASes differ in geographic size (expanse) and economic parameters (e.g., transit prices).

ASes connect with one another mostly through two types of relations: customer-provider (or "transit") links and settlement-free peering links. Under the customer-provider relationship, the provider is responsible for connecting the customer with the rest of the Internet. The provider may itself have a transit provider and so on. Settlement-free peering (subsequently referred to as "peering" for brevity) is more subtle than a customer-provider relationship. In peering, two ASes (or peers) agree to exchange traffic between themselves and their customers over a shared link. Peers do not pay each other for this exchange; however, they share the cost of the link. For example, ASes peering at an Internet Exchange Point (IXP), use the IXP's infrastructure for peering. Thus, the IXP's infrastructure forms the shared link between the peers. While they do not pay one another for the traffic that they exchange among themselves, they pay the IXP for usage of its infrastructure.

Peering is typically carried out with the objective of saving transit costs by diverting traffic from customer-provider links to peering links. ASes generally follow broad rules, referred to as "peering strategies" to determine their peering links. Examples of such rules-of-thumb include *Open* (peer with all co-located ASes except customers), *Selective* (peer with only those ASes that have similar traffic volume), *Restrictive* (do not peer with anyone unless that is necessary to maintain global reachability). The highest level of the Internet consists of a clique of approximately 15 ASes fully meshed among themselves through peering links. This clique is known as the "Tier-1" clique and these ASes are known as "Tier-1 transit providers". Tier-1 providers do not require a transit provider as they can reach the entire Internet through their customers and peers. Figure 1 provides an illustration of these topological concepts. In Figures 1a and 1b x, y, z, w and T are ASes; T is a Tier-1 provider, x and y are transit providers, and w and z are stubs. Figure 1a shows the flow of traffic between transit providers and stubs through the Tier-1 provider. In Figure 1b, the introduction of a peering link between x and y causes the traffic to flow over a different path, avoiding the Tier-1 provider altogether. This results in reduced transit costs for x and y. Figure 1c illustrates the concept of the Tier-1 clique in the Internet. The ASes shown are Tier-1 providers, which form a complete mesh among themselves through peering links. Traffic between their customer trees is routed through these peering links.

1.2 Contemporary Peering Practices

In this section we briefly describe how typical large ASes carry out peering in practice.

1.2.1 Identification of potential peers

Identification of potential peers is the first step in peering. One of the ways that operators use to find potential peers is to analyze traffic flow data collected locally using NetFlow to identify other ASes with whom they exchange significant volume of traffic. Typically, this analysis only informs about traffic that is generated and consumed within the AS (and exchanged with the potential peer), and does not include traffic from the AS' customers (and potential peer's customers) that may be exchanged over the peering link after link formation.

1.2.2 Selective peering criteria

Since Tier-2 NSPs are in the transit business, they prefer other ASes to be their customers instead of peers. Thus, most of them adopt *selective* criteria of some sort to deter peering applications by smaller ASes. For example, many large NSPs require their peers to be co-located at multiple geographic locations, maintain a lower bound on the traffic exchanged, 24×7 NOC, a lower bound on the capacity of the physical network, etc. NSPs almost

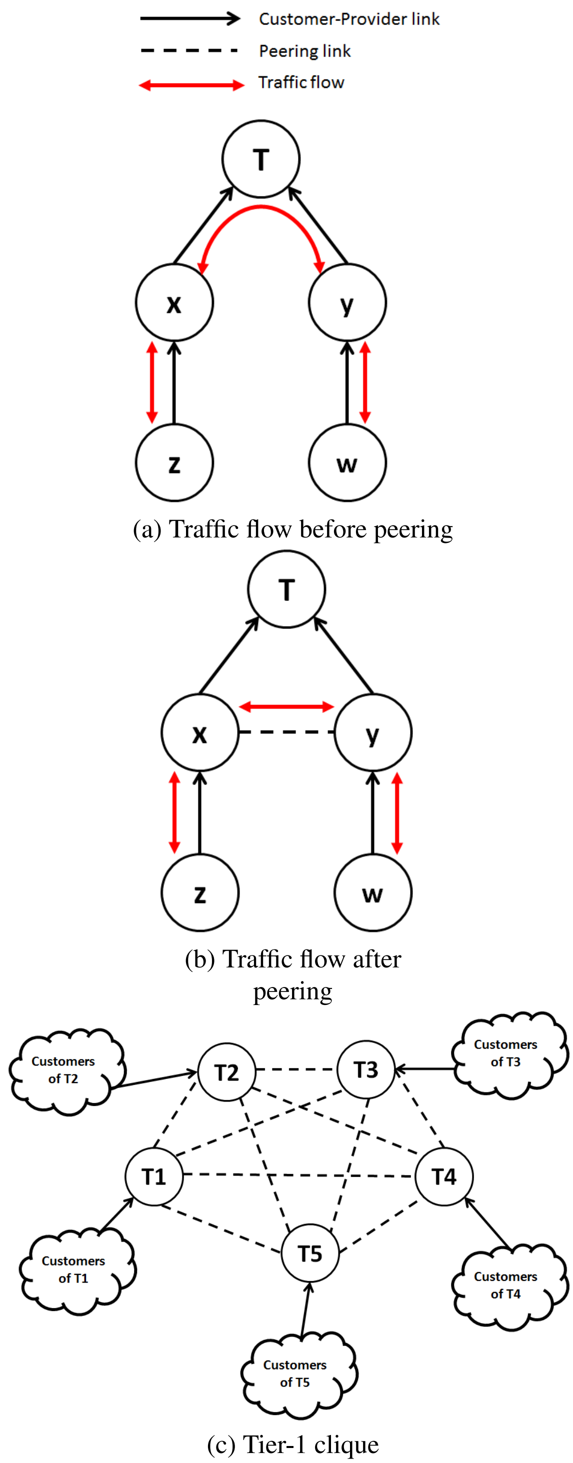


Figure 1: Connectivity variants in the interdomain network

always deny peering to their existing customers, while many NSPs also deny peering to their previous customers[1].

1.2.3 Preventing asymmetric benefits

Peering is supposed to be mutually beneficial. Most ASes involved in peering would expect that the cost of peering would be borne equally by both parties. Furthermore, many ASes, typically large ISPs and NSPs, demand that the benefits derived by both parties in a peering relationship be roughly equal. For example, NSPs do not want their competitors to free-ride their networks through peering. NSPs use traffic exchanged over the peering link as a proxy for the benefits derived from a peering relationship. In order to limit the asymmetry of benefits, NSPs generally require that the ratio of inbound to outbound traffic be within certain bounds. If the bound is set to 1 then the traffic in both directions should be equal, if it is set to a value less than 1 then the inbound traffic should be less than the outbound traffic and vice versa. Analysis of peering policies published by large NSPs and our discussions with network operators reveal that contemporary values for this bound, in general, are between 2 and 5 [3, 13, 4, 1]. This allows an NSP to form settlement-free relationships with most content providers but excludes a few "hyper-giants" [66] with whom the inbound traffic would be orders of magnitude greater than the outbound traffic.

1.2.4 Paid peering

In general, NSPs form settlement-free peering relationships with all other ASes which satisfy the requirements of their peering policies, while offering paid peering relationships to those which do not do so. Paid peering is similar to a conventional customer-provider relationship, however, whereas a transit provider is responsible for providing a customer connectivity to the entire Internet, a paid-peering provider only offers access to its customers, in addition to itself. Correspondingly, the price for paid-peering is lower than conventional transit prices. Little public information is available about the modalities of paid-peering

[1]Previous customers are denied peering to dissuade existing customers from terminating their contracts and doing the same.

as well as prices for paid-peering, as details of most relationships are held private through non-disclosure agreements.

1.3 Organization

This thesis is organized as follows. We provide a description of the related work in Chapter 2. Chapter 3 describes our baseline model, GENESIS, which we use to model formation of peering links, traffic flow and economics in the interdomain network. Subsequent chapters use different variations of the baseline model to address different questions. Each chapter describes the variations as well. Chapter 4 addresses the fundamental problems in peering, e.g., what precludes the development of methodical quantitative approach to find the optimal set of peers, etc. We provide details of a data analysis study of the peering ecosystem from August 2010 to August 2013 in chapter 5. Chapter 6 discusses a plausible explanation for the gravitation of Internet transit providers towards Open peering policy. In chapter 6, we propose two new peering strategies to mitigate the effects of large-scale Open peering and carry out more precise cost-benefit-analysis for each peer. Chapter 7 provides major conclusions from the thesis and an outlook for potential questions in the area for the future.

CHAPTER II

RELATED WORK

There is a large body of research literature dedicated to the study of the structure of the Internet interdomain network. These works, which mostly involve empirical studies of the interdomain network, include inference and classification of inter-AS relationships, study of static topological properties of the interdomain network e.g., degree distribution, diameter, etc., measurement and link discovery techniques, exploration of the evolution of the network over time, etc.

2.1 Internet Topology at the AS level

Faloutsos et al. propose that the interdomain network follows a power-law distribution [46]. However, Chen et al. argue that the interdomain network may not be "scale-free" because of the difficulty in observing all links [31]. Gao proposes a model to classify inter-AS relationships acquired through BGP data into customer-provider, sibling and peering relationships by exploiting the "valley-free routing policy" of the Internet [50]. Zhang et al. prpose a list of resources that can be exploited to get more data about the topology of the network [110]. Oliveira et al. evaluate different AS-relationship inference methods using case studies of different ASes. [91]. Dimitropoulos et al. propose some heuristics to discover inter-AS relationships and s [42]. Luckie et al. continue this line of work and propose heuristics which are better at discovering peering relationships from BGP data [79]. Knight et al. explore the PoP-level topological data of more than 200 ASes and argue that the Internet topology does not conform to any specific model so far [65]. Gill et al. show that the peering strategies and expansion of large content providers results in a relatively "flat" Internet [52].

2.2 Evolution of the AS-level Internet topology

Amogh et al. study the evolution of the Internet topology in terms of its growth and rewiring from 1998 to 2010 [37]. Their analysis shows that despite exponential growth in the population of the ASes, the average path length in the network is practically constant, implying that the network densifies over time. They also find that a positive correlation exists between the customer degree of a provider and attraction and repulsion for future customers. They also analyze the regional growth of the Internet and conclude that the growth of the Internet in Europe exceeds all other regions of the globe. Shavitt et al. study the evolution of the topological actions by large content providers from 2006 to 2011 [98]. They show a densification of links between large content providers and non-Tier1 nodes of the interdomain network.

2.3 Interconnections in the Internet from an industrial organization perspective

Many works focus on Internet economics from industrial organization perspective. Faratin et al. show that changing conditions have resulted in a more diverse and complex interconnection market in the Internet [47]. Ghodsi et al. advocate that the Internet move from the current point-to-point connection architecture to information or content centric architecture [51]. Laffont et al. develop a framework for competition in the Internet transit market [68]. Hermalin et al. explore the question about who decides which network carries the transaction in an envrionment where traffic traverses more than one intermediary network [61].

2.4 Network formation Models

2.4.1 Graph Theoretic Models

Zegura et al. carried out one of the first works in this domain and proposed graph generation models as well as metrics to compare the graphs generated by models in this category [108, 109]. Various graph theoretic models aim to reproduce observed Internet topological properties (e.g., power-law degree distribution [46]) [105, 107, 106]. Another class of models take a bottom-up approach [70], modeling the optimization objectives and constraints of individual ASes, to create graphs that have the same topological properties [70, 45, 28, 34].

2.4.2 Agent-based Computational Models

Agent-based computational models that simulate the dynamics of the network formation process, capturing the asynchronous and decentralized process through which nodes adjust their connectivity, have also been proposed in the literature and used for various studies. The model by Holme et al. [62] is similar to our computational model but it does not include peering and realistic routing. The model of Chang et al. [29] uses hard-wired strategies for provider and peer selection, among other differences. The model of Dhamdhere et al. [41] is more similar to our model but it assigns a specific function to each node (e.g., content provider) and it focuses on the differences between two Internet instances (hierarchical versus "flat"). Lodhi et al. propose GENESIS, another computational agent-based model for modeling interdomain network formation, traffic flow and economics [74].

2.4.3 Game-theoretic Models

A large body of work on game-theoretic network formation models exists in the computer science and economics literature. We refer the interested reader to two recent books [56, 64]. Those models capture the objectives and potential strategies of each node, as players in a non-cooperative game, and they focus on proving the existence of (typically many) equilibria. The need for mathematical tractability, however, requires significant simplifications (such as lack of geographic constraints, simple cost functions, or uniform traffic flow between nodes. Consequently, the resulting networks are typically simple graphs, such as rings, trees or other regular structures.

2.5 The role of IXPs in the Interdomain Network

IXPs have played a key role in changing the landscape of Internet interconnection by providing facilities for large-scale peering. The nature and role of IXPs has been the subject of many recent works. Augustin et al. carry out active probing to determine IXP memberships [23]. Chatzis et al. highlight the role of IXPs not only in the context of the Internet interconnections, but also in the context of data centers, cloud computing and SDN [30]. Ager et al. analyze membership, interconnection and traffic flow data from a large European IXP [19]. Gupta et al. present a possible implementation of a Software-Defined-Internet-Exchange to take advantage of SDN [57].

2.6 Properties of the Interdomain Network Traffic Matrix

Accurately measuring, estimating and modeling traffic matrices is key to ensuring stable peering relationships. Medina et al. present a taxonomy of IP traffic matrices [83]. The thesis by Chang presents various economic-based approaches to measuring and modeling traffic matrices [27]. Labovitz et al. show that the video constitutes a significant fraction of Internet traffic today and that 80-20 rule also exists in the Internet traffic generation and consumption market [67]. Roughan et al. show how to do traffic engineering with only estimated traffic matrices [95]. Gursun et al. explore which ASes in the interdomain network hierarchy are in a better position to infer the elements of the interdomain traffic matrix [95].

2.7 Internet Economics

Internet economics is a wide-ranging subject covering many areas e.g., pricing, cost-benefit-analysis techniques, market-share analysis, determination of tiered-pricing structure, profitability under different interconnection strategies etc. We identify some representative works in this domain. Hosanagar et al. contend that CDNs will have to lower prices to stay competitive in the connectivity market [63]. Motiwala et al. argue that signifcant cost reductions can be achieved through re-routing a relatively small portion of traffic [85]. Stanojevic et al. discuss how customers generate costs for access providers [101]. Dimitropoulos et al. discuss the 95th percentile billing method widely used in the Internet [44]. Shakkottai et al. explore the interaction between multiple ISPs through price setting when they may or may not be competing for the same customers [97]. Valancius et al. show that optimal utility by transit providers can be achieved by establishing only a few pricing tiers [104]. Gyarmati et al. analyze backbone cost-sharing policies by operators to determine which policy gives optimal results [59]. Hasan et al. develop an optimization model to optimize the placement of caches to reduce costs for CDNs [60]. Dhamdhere et al. explore if ISPs can be profitable without violating the net neutrality principles [40]. Castro et al. propose T4P, a hybrid routing scheme allowing peers to use common upstream links to reduce transit costs [16]. Lodhi et al. carry out a data analysis study of the peering ecosystem based on the data published in PeeringDB from August 2010 to August 2013 [18].

2.8 Economics of Peering Interconnections

There has been much prior work on economic analysis of peering in the interdomain network covering various aspects of the peering ecosystem including pricing, paid-peering, utility optimization heuristics, policy adoption, etc. An extensive line of research has taken an analytical approach to explore paid-peering. Shrimali et al. study linear pricing schemes for paid-peering between two providers [99]. Dhamdhere et al. propose a quantitative framework to determine the value of a peering link for both peers involved [39]. Ma et al. analyze the use of Shapley value for revenue distribution among peers [82]. There is also prior work on the game-theoretic analysis of settlement-free peering and transit vs. peering [25, 73, 24, 22, 84, 35]. However, for reasons of mathematical tractability, these models often study networks with a small number of players. Therefore, many complexities that arise out of the interaction of a large number of autonomous agents do not appear in these works. Furthermore, they also ignore many real-world features of the interdomain network, e.g., a highly skewed traffic matrix, geographic co-location constraints, ratio-based peering policies, capacity constraints of IXP ports, complex non-linear pricing structure, etc. Another line of work has focused on models in which ASes select transit providers, settlement-free peers or peering policies based on economic factors and other constraints to optimize their utility [77, 45, 28, 29]. Lodhi et al. attribute the gravitation of Internet transit providers towards Open peering to myopic and selfish decisions by ISPs [77]. They also propose cost-benefit-analysis based peering strategy [76]. Norton provides an excellent discussion of various aspects of peering practices from an operations aspect [88].

Gyarmati et al. propose an analytical framework to quantify a fair price that should be paid by either a content provider or ISP (access provider) if they form a premium paid-peering interconnection [58]. Their model assumes performance benefits to be gained from premium peering and churn among the customers responding to performance variation. Thus, both content providers and access customers have an incentive to engage in premium peering to acquire more customers. They compute a Nash bargaining solution to determine which side of the peering interconnection should pay and how much to form a stable peering link. They also create an online tool to do these calculations for custom scenarios [17]. Our models in this thesis operate at the scale of the interdomain network, modeling the interactions of multiple autonomous systems, while ignoring activity within the ASes. Whereas, the framework of Gyarmati et al. models the actions of individual customers within access ISPs and revenue from individual streams within content providers, in a specific geographic market. While this is promising work in the right direction, there are still significant challenges to be overcome particularly for parameterization of such models. Additionally, in some geographic regions, access ISPs offer Internet access bundled with other services, e.g., cable television and telephone, making it hard to assess the decisions of the individual customers. Furthermore, sometimes the customers are also obliged to keep their subscriptions with their ISPs for extended periods of time under contract. Finally, the bargaining power of content providers is an open question since there is very little competition at the level of access ISPs.

CHAPTER III

GENESIS: AN AGENT-BASED MODEL OF INTERDOMAIN NETWORK FORMATION, PEER SELECTION, TRAFFIC FLOW AND ECONOMICS

This chapter describes the basic version of our network formation model - GENESIS. Different variants of GENESIS are used in subsequent chapters of this thesis. While the variants differ in some aspects, the overall structure of our model remains the same. We explain each variation in its corresponding chapter.

3.1 Model Description

We consider a population of N nodes (representing Autonomous Systems) which interconnect through two types of links: customer-provider and peering. Each node has the following attributes: a set of locations in which it is present, an amount of traffic it sends to and receives from every other node, and certain economic parameters, such as the transit price it would charge to its potential customers at a given location.

We next describe each component of GENESIS in more detail. A complete description of the model, with a longer justification, is available at a technical report [5]. The source code for the simulator that executes GENESIS is available at the same URL.

Geographical presence: There are G_M locations, and a node x is present at a set $G(x)$ of locations. These locations are roughly analogous to Internet Exchange Points (IXPs). Two nodes *overlap* if they share at least one location. For node x, $O(x)$ denotes the set of networks that overlap with x. A link between two nodes can be formed if they overlap.

Traffic matrix and transit traffic: The element T_{xy} of the N-by-N interdomain traffic matrix T denotes the average traffic volume generated by node x and consumed by node

y. Overall, x generates traffic $V_G(x)$ and consumes $V_C(x)$. T_{xx}=0, i.e., we do not capture the local traffic within a network. The *transit traffic* $V_T(x)$ of x is the traffic volume that is neither generated nor consumed by x – it only passes through x enroute to its destination. The transit traffic of a node depends on the underlying network topology and the routing algorithm. Even if the interdomain traffic matrix T is constant, the transit traffic of a node may change as the underlying topology changes. The total traffic volume of a node $V(x)$ is given by the following expression:

$$V(x) = V_C(x) + V_G(x) + V_T(x) \tag{1}$$

Economic attributes: The economic attributes of a node include its transit prices (one for each location it is present at).

Transit cost: Let x be a transit customer of y, and let $P_y(x)$ be the *lowest* transit price of y across all regions in which x and y overlap. If $V_P(x)$ is the traffic exchanged between x and y, then the transit payment from x to y is:

$$TC(x) = P_y(x) \times V_P(x)^{\tau} \tag{2}$$

where τ is a transit traffic exponent that captures the *economies of scale* observed in practice. The transit revenue $TR(y)$ of y is simply the sum of transit costs paid by all customers of y.

Peering cost: Nodes engaging in settlement-free peering relations share the underlying peering costs. There are two primary mechanisms for peering — private and public — that have different cost structures. If the traffic exchanged between two peers is less than a threshold Ψ they peer publicly at an IXP, otherwise they peer privately. In public peering, nodes exchange traffic over a common switching fabric at an IXP, aggregating traffic from different peering sessions through the same port, whereas in private peering they set up a direct link with each peer.

Private peering cost: Let $V_{PP}(x, y)$ be the traffic exchanged between node x and its peer y over a private peering link. The total cost of private peering for x is given by:

$$PC_{prv}(x) = \alpha \times \sum_{y} V_{PP}(x, y)^{\beta} \tag{3}$$

where α is the peering cost per Mbps and β is the peering traffic exponent that accounts for the corresponding economies of scale.

Public peering cost: Let $V_{PP}(x, z)$ be the traffic exchanged between node x and its peer z over the public peering infrastructure. As x aggregates all its public peering traffic over the same port, the corresponding cost is:

$$PC_{pub}(x) = \alpha \times (\sum_{z} V_{PP}(x, z))^{\beta} \tag{4}$$

Fitness[1]: The fitness of a node represents its net profit,

$$\pi_x = TR(x) - TC(x) - PC_{pub}(x) - PC_{prv}(x) \tag{5}$$

If a node is a stub, i.e., a node without any customers, the first term is zero and the node's fitness will be negative.

Peering: Two nodes x and y are potential peers if they satisfy two *peering criteria* — x and y overlap geographically, and they do not have an existing customer-provider relationship. Additionally, a node x uses a *peering strategy* $S(x)$ to determine which of its potential peers it wants to peer with. Unlike provider selection, where a customer unilaterally chooses its provider, peering is a bilateral decision process. Thus, two potential peers x and y can peer iff the constraints of both $S(x)$ and $S(y)$ are satisfied. Depeering, however, is a unilateral decision by one of the peers. By default, GENESIS uses three peering strategies described in section 3.2.

Provider selection: A node must have a transit provider if it cannot reach all other nodes in the network via its peers and customers. Node x selects a provider y if: *(a)* x overlaps with y, *(b)* y is "larger" than x (explained next), *(c)* y is not a peer of x, *(d)* y is

[1] *Fitness and Utility are used interchangeably in this thesis.*

not a customer of an existing peer of x, and *(e)* y is the least expensive among all nodes that satisfy the previous constraints. We say that a node y is larger than a node x if y is present in at least as many locations as x, and it carries more transit traffic than x. If a node x cannot find a provider that fulfills the previous criteria, then x becomes a $tier - 1$ (T1) AS. In order to ensure a connected network, $T1$ nodes form a clique using peering links, even if they do not overlap.

Routing: In GENESIS, interdomain routing follows the shortest path subject to two common policy constraints: "prefer customer over peer over provider links" and satisfy the "valley-free" routing property.

Initial topology: To create the initial network topology, we select nodes sequentially and at random. For a selected node x, we determine its provider randomly from the set of nodes that *(a)* overlap with x, *(b)* are not in the customer tree of x, and *(c)* have greater geographic expanse than x. If we cannot find a provider for a node, then it joins the clique of tier-1 networks.

Network formation process: An execution, or sample path, of GENESIS proceeds in discrete time units called *iterations*. In each iteration, every node *plays* asynchronously once. The order in which nodes play during an iteration is determined at the start of the sample path, and it remains the same throughout that sample path. Every time a node plays, it carries out the following actions: *(a)* Examine depeering with existing peers, *(b)* Examine peering with new peers, *(c)* Provider selection, and *(d)* Peering strategy update. At the end of each iteration, we recompute the fitness of each node. If none of the nodes has adjusted its connectivity and peering strategy in that iteration, then it is easy to show that there will be no changes in subsequent iterations, and we say that GENESIS has reached an *equilibrium*.

The *state* of the network at any point in time can be defined based on the connections and peering strategy of all nodes. Two states **A** and **B** are distinct if they differ in terms of the underlying network topology or the peering strategy of one or more nodes. Even if we start with the same population of nodes and the same initial topology, two sample paths can result in two distinct equilibria as a result of different playing orders.

3.2 Default Peering Strategies

The peering strategies that we consider in the default model are the following three:

1. *Restrictive*: A node that uses this strategy does not peer with any other node unless if that is mandatory to maintain global reachability ("peering-by-necessity"). This peering strategy is followed only by T1 nodes; those nodes form a clique to keep the network connected.

2. *Open*: A node that uses this strategy agrees to peer with any other node that it overlaps with (except direct customers). In the default GENESIS model, the Open peering strategy is followed by stubs because those nodes aim to reduce their transit costs by peering with as many other nodes as possible.

3. *Selective*: A node x that uses this strategy agrees to peer with node y if $\frac{V_x}{V_y} \leq \sigma$ ($\sigma > 0$). In practice, there is a wide range of Selective peering strategies with several additional constraints and parameters (e.g., a minimum link capacity or a minimum number of points-of-presence) [1]. Our Selective strategy is only a model that aims to capture the essence of those requirements through a simple formula and single parameter σ. The Selective peering strategy in the default GENESIS model is followed by non-T1 transit providers.

3.3 Scalability and Parameterization based on Real World Data

GENESIS is currently parameterized based on the statistical characteristics of real world parameters. GENESIS is capable of directly incorporating real world data, e.g., topology from BGP advertisements, geographic co-location from PeeringDB, etc. However, scalability of the current implementation restricts it to model the entire interdomain network. Increasing the scalability of GENESIS is one of the key items for our future work.

If GENESIS' implementation can successfully model the entire interdomain network, certain short-term micro effects, e.g., formation of a peering link between certain ASes, may be predicted. However, uncertainty in some parameters, particularly traffic flows and the timing of AS actions can limit the ability of GENESIS to predict all effects with complete accuracy.

CHAPTER IV

COMPLEXITIES IN INTERNET INTERDOMAIN PEERING

We explore the fundamental aspects of peering in this chapter. We explore the main complexities in identifying new peers, choosing the optimal set of peers among a given set of peering candidates and evaluating existing peers over time. As explained in Chapter 1, most ASes use simple rules-of-thumb to make such decisions. We explore the obstacles in developing a methodical approach to making such decisions. We address these questions for a specific class of ASes, the *Tier-2 Network Service Providers (NSPs)*. We choose to focus on NSPs (or transit providers) because they appear in all three AS roles in the interdomain network, namely providers, customers and peers, simultaneously. Additionally, their "selective" peering policies are more complex than the simpler "open" and "restrictive" policies of stubs and Tier-1 providers respectively. We focus on three major sources of complexity which we evaluate separately:

1. Limited ability to determine and accurately predict traffic flows.
2. Limited ability to accurately forecast the effect of peering on utility owing to a complicated pricing structure.
3. Infeasibility of determining the optimal set of peers because of the combined effects of topology and routing policy.

4.1 Variation of GENESIS and Parameterization

We vary our basic model GENESIS presented in Chapter 2 for the purpose of this evaluation as follows.

Peering Policies: Nodes form peering relationships based on their peering policies which are assigned to them based on their status in the network hierarchy. We use the following peering policies in our model:

1. *Restrictive:* Nodes using this strategy do not peer with any other node unless required to ensure global reachability. Restrictive policy is assigned to Tier-1 NSPs.

2. *Open:* Nodes using this policy peer with all co-located nodes. All stubs use this peering policy.

3. *Selective:* Selective policy is used by Tier-2 NSPs. A node i using Selective peering policy will agree to peer with another node j if the traffic exchanged between them conforms to the following condition:

$$\frac{T'_{ji}}{T'_{ij}} \leq \sigma \tag{6}$$

   where σ is a traffic ratio constraint which is uniform and constant across all nodes using Selective policy[1] and T'_{ij} is the actual traffic exchanged over the peering link between i and j, L'_{ij}. It is difficult to estimate T'_{ij} (and vice versa) without actually forming L^p_{ij}. Therefore, nodes use local traffic, T_{ij}, instead of actual traffic, T'_{ij}, to identify peers and verify policy constraints prior to link formation. All our players of interest use Selective peering policy.

Since peering is a bilateral relationship both peers must conform to each other's peering policies before a link is formed. The set of peers of a node i is denoted by $F(i)$.

Transit Cost and Revenue: Traffic exchanged over customer-provider links is metered. For the traffic $(T'_{ij} + T'_{ji})$ exchanged between i and its provider j over the link L^t_{ij}, i incurs a transit cost $TC(i, j)$ given by:

$$TC(i, j) = P^t(T'_{ij} + T'_{ji}) \times (T'_{ij} + T'_{ji}) \tag{7}$$

[1] In reality, Selective peering policies have additional constraints, e.g., co-location at more than one location, minimum requirements for the volume of traffic exchanged, etc. However, we only use traffic ratios for simplicity.

where $P^t(T'_{ij} + T'_{ji})$ is the price ($/Mbps) for the corresponding traffic volume. The total transit cost of i is given by:

$$TC(i) = \sum_{j \in P(i)} TC(i, j) \tag{8}$$

The transit revenue, of i, $TR(i)$, is the sum of the costs incurred by the customers of i for their transit links with it.

Peering Costs at IXPs: Players utilize the *ports* at the IXPs to peer with one another and exchange their peering traffic. IXP costs are fixed monthly recurring costs based on the number and type of ports that a node has acquired at the IXP. When i peers with j, it checks if any of its existing IXP ports with leftover capacity $T'_{ij} + T'_{ji}$ and routes over that port, otherwise it acquires a new port of minimum size required to accommodate the traffic.

Let $p_c(i)$ be the number of ports of capacity c Mbps being utilized by i and $E^p(c)$ be the price of a port with capacity c. Then the total settlement-free peering cost of i, $IC(i)$ is given by:

$$IC(i) = \sum_{c} P^p(c) \times p_c(i) \tag{9}$$

Paid Peering: There is no publicly available data about paid-peering prices. Therefore, we use anecdotal evidence gathered from peering coordinators and various online peering discussions [9] to set the paid-peering price for traffic volume t to one half that of the transit price for the same traffic volume. Finally, both paid-peers use a private interconnect at the IXP to exchange their traffic separate from settlement-free peering traffic. For simplicity, the private interconnect incurs a cost equal to the cost of the public interconnect with the same capacity. The paid-peering revenue and costs for node i are denoted by $PC(i)$ and $PR(i)$ respectively.

Analysis for a paid-peering relationship is carried out only if one of the peers does not satisfy the other's peering policy requirements. For example, if j does not satisfy

i's policy constraints, then i carries out a cost-benefit-analysis of accepting j as its paid-peering customer, based on traffic $T_{ij} + T_{ji}$. The cost-benefit-analysis involves calculating the effect of moving the traffic $T_{ij} + T_{ji}$ from the link on which it is currently being routed[2] to the proposed link L_{ij}^{p}. i offers j to become a paid-peering customer if the cost-benefit-analysis indicates that acquiring j would increase its utility. j upon receiving the offer carries cost-benefit-analysis at its own end and accepts the offer if its analysis shows that its utility will also increase. On the other hand, if i does not satisfy j's peering policy, then an offer to become a paid-peering customer is made by j and a similar analysis is carried out, albeit with roles reversed. Thus, a paid-peering relationship is formed if and only if cost-benefit-analysis by both nodes shows that their utility will increase as a result of the relationship. Note that the actual cost may differ from the one estimated by cost-benefit-analysis because the actual traffic $(T'_{ij} + T'_{ji}) \geq (T_{ij} + T_{ji})$.

Utility: The utility of a player i is determined by its peering links, the traffic traversing those links and how this traffic is distributed over IXP ports. The utility of i is given by:

$$\pi_i = TR(i) + PR(i) - TC(i) - PC(i) - IC(i) \tag{10}$$

Note that although the transit prices and the traffic matrix $\boldsymbol{T}$ are constant, the underlying topology changes as i chooses different peers. Hence, the costs, revenues and utilities may change as the topology changes.

The objective of player i is to maximize π_i through peering.

Network Formation: Starting from a random population, we create an initial topology by assigning each node (except Tier-1 nodes) with at least one transit provider using the constraints described in the default model. It produces a network hierarchy similar to that of the Internet at scale, without any peering links. Tier-1 nodes are not assigned transit providers and they form a complete mesh of peering links among themselves similar to the Tier-1 ASes in the Internet.

[2]The current link carrying this traffic may be a transit link or an existing settlement-free or paid-peering link.

Table 1: Transit and Peering Prices

Transit & Paid Peering			IXP Peering	
Traffic t (Gbps)	Transit Price (\$/Mbps)	Paid Peering Price (\$/Mbps)	Port size (Gbps)	Price (\$/month)
$t < 1$	6	3	0.1	100
$1 \leq t < 10$	4	2	1	800
$10 \leq t < 100$	1	0.5	10	1700
$t \geq 100$	0.4	0.2	100	7820

After the creation of initial topology, network formation proceeds in discrete iterations called *rounds*. In each round all Tier-2 NSPs play once, one at a time. When a Tier-2 NSP i plays, it actively seeks to form peering relationships with other nodes, while the other nodes only evaluate incoming peering requests.

4.1.1 Parameterization

The values for our parameters are given in Tables 1 and 2. Table 1 shows the median prices for different traffic ranges and port sizes at IXPs, reported by TeleGeography [102] and the websites of the following IXPs: AMS-IX [21], DEC-IX [36], LINX [72]. We consider high-end pricing at IXPs for the same port sizes so that the performance is comparable under transit and IXP peering. We ignore one-time fixed costs, e.g., initial IXP membership costs.

4.2 Traffic Uncertainty in Peering

In this section we evaluate the first source of complexity, i.e., the effect of imperfect traffic prediction prior to establishing a peering link. In section 1.2.1 we described that ASes

Table 2: Input Parameters

Parameter, Symbol, Description	**Value**	**Explanation**
Number of ASes N	2000	Time constraints for the simulation
Number of geographic locations G_{Max}	100	Based on approximate ratio of IXPs to peering networks in the Internet. PeeringDB ratio 18.55. Model ratio 20.0 [14]
Geographic expanse distribution	Zipf(1.6)	Based on data about number of participants at each IXP collected from PeeringDB [14]. IXP locations are randomly assigned to each node.
Maximum points-of-presence for an AS	15	
Generated traffic distribution	Zipf(1.2)	It generates a heavy-tailed distribution consistent with the behavior reported in [26], [48] & [66]. With this distribution, 0.1% of the ASes generate nearly 30% of the total traffic.
Consumed traffic distribution	Zipf(0.8)	Produces heavy-tailed distribution of incoming traffic, similar to internally measured traffic distribution at a large US public university.
Maximum consumed traffic	8 Tbps	Estimated Comcast traffic [92]. Consumed traffic of a node is proportional to its points-of-presence, the rationale being that a node with large expanse will also have a large number of access customers.
Selective peering ratio σ	3.0	Peering policies of different NSPs, e.g., [3, 13, 4, 1]
Multihoming Degree	2	Fixed for all non-Tier1 nodes for simplicity. [38]

typically employ NetFlow to identify its potential peers. We discuss each of these sources of uncertainty as follows.

4.2.1 Limited Information from NetFlow

Consider the network shown in figure 2 where a Tier-2 NSP i attempts to determine if j is a potential peer. In order to identify potential peers, a Tier-2 NSP i employs NetFlow to analyze the origin and destination of its local traffic, i.e., traffic generated within i and consumed at another co-located AS j and vice versa, i.e., $\hat{T_{ij}}$. i also estimates the ratio of inbound to outbound traffic T_{ji}/T_{ij} using this data. However, this analysis ignores the fact that x and y, which are customers of i and j respectively, may also exchange traffic over the proposed link L_{ij}^{p}. Thus, the maximum traffic that may be exchanged over L_{ij}^{p} is:

$$max(T'_{ij} + T'_{ji}) = \hat{T_{ij}} + \hat{T_{iy}} + \hat{T_{jx}} + \hat{T}_{xy}$$

In this case, while NetFlow informs i that $\hat{T_{xy}}$ flows through its network, i cannot determine if this traffic also flows through j. Even after employing other tools, e.g, *traceroute* and analysis of *BGP* announcements, i cannot be certain about the path taken by $\hat{T_{xy}}$ because of asymmetric routing and multihoming in the interdomain network. This uncertainty may negatively affect the peering decisions of i as follows:

Premature rejection: Let

$$T_{ij} + T_{ji} \ll T'_{ij} + T'_{ji}$$

Then i may assume that it does not exchange a significant volume of traffic with j and prematurely decide not initiate peering negotiations. Whereas, if it had accurate estimates of the traffic that would flow over the peering link, it would have moved down the check list of other peering policy requirements.

Premature acceptance: Let

$$\frac{T_{ji}}{T_{ij}} \leq \sigma \ \ , \ \ \frac{T'_{ji}}{T'_{ij}} > \sigma$$

In this case, i may peer with j assuming that j satisfies its traffic ratio requirement. However, once the link is formed and traffic starts flowing over L_{ij}^{p}, i will determine that its peering requirements are not being met by j. Such situations, which arise out of inaccurate estimates of traffic prior to link formation, are one of the causes of peering conflicts in the real world.

4.2.2 Dynamic Routing

The interdomain network, constituting its physical structure and traffic flows, self-organizes itself through the collective actions of local and (in many cases) autonomous interactions

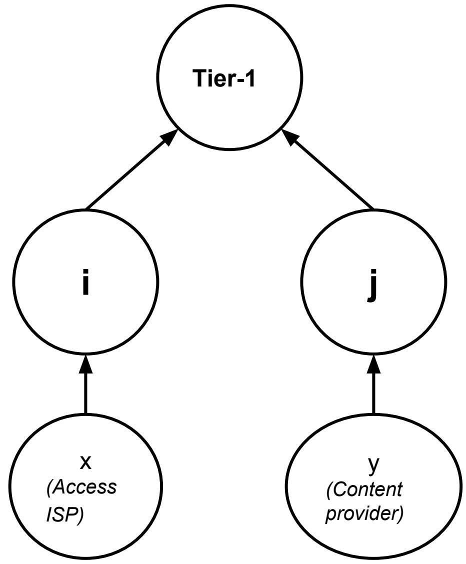
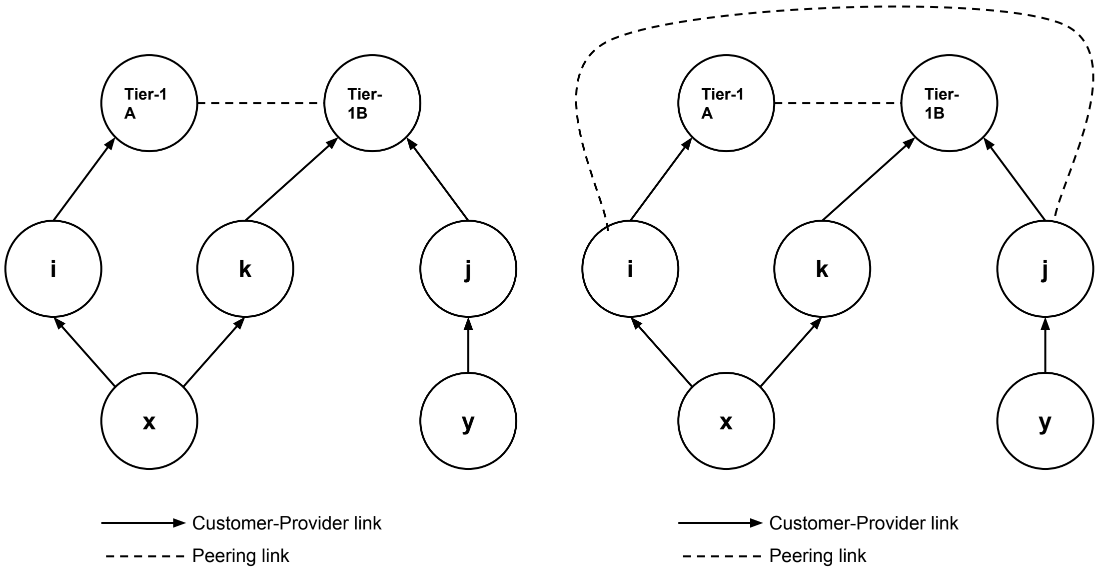


Figure 2: Limited Information from NetFlow

of the ASes. This results in a complex network where peering links between different ASes may have non-local effects, i.e., they may affect the traffic flows over other ASes and links [77]. Once a peering link is formed by i, its customers (and those of the peer, if it has any) may update their routes given the changes in the network. Assuming default BGP configuration to choose the shortest routes, these updates may cause customer traffic which was not previously routed through i to flow through i and vice versa. Both scenarios have a direct impact on the peering relationships of i and its utility. We illustrate both cases as follows.

Addition of traffic: Consider the network shown in figure 3. Prior to formation of L^p_{ij}, as shown in figure 3a, traffic $\hat{T}_{xy}$ from its customer x bypasses i as route $x \to k \to Tier1\,B \to j \to y$ is one hop short of the route $x \to i \to Tier1\,A \to Tier1\,B \to j \to y$. Since this traffic bypasses i, it has no way of measuring it. Additionally, x does not know the route taken by this traffic. However, once the peering link L^p_{ij} is formed, i offers a shorter route $x \to i \to j \to y$ than the one previously chosen by x. Hence, i may experience an upsurge in customer traffic, which it could not predict prior to the execution of its peering decision.

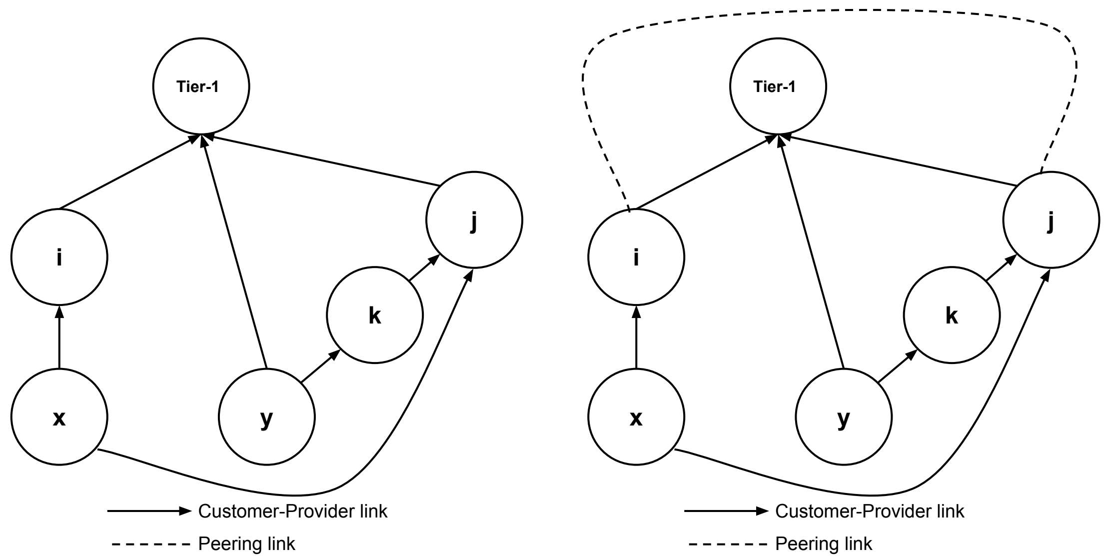


(a) Before formation of L_{ij}^p (b) After formation of L_{ij}^p

Figure 3: Addition of traffic after formation of a peering link

Reduction in traffic: Consider the network shown in figure 4. Prior to formation of L_{ij}^p, as shown in figure 4a, traffic $\hat{T}_{xy}$ from its customer x flows through i taking route $x \to i \to Tier1 \to y$. However, once the peering link L_{ij}^p is formed, i no longer routes traffic through the $Tier1$ node because of "prefer-peer-over-provider" routing policy. This, however, increases the path length for $\hat{T_{xy}}$ as it is routed over the path $x \to i \to j \to k \to y$. Therefore, x routes traffic away from i to its second provider j offering it a shorter path $x \to j \to k \to y$. Hence, i may experience a decline in customer traffic, which it could not predict prior to formation of the peering link. Note that these path-selection decisions may take place autonomously without any human intervention.

Although i can infer the topology of the interdomain network using different inference techniques, these techniques are limited in that they cannot accurately discover peering links and do not inform about the routes adopted by specific traffic flows [49, 80].



(a) Before formation of L^p_{ij} (b) After formation of L^p_{ij}

Figure 4: Reduction in traffic after formation of a peering link

4.2.3 Computational Results

We illustrated the main sources of traffic uncertainty using simple examples in sections 4.2.1 and 4.2.2. In this section we explore, through large-scale computational simulations based on our model of section 4.1, the extent to which these complexities manifest themselves in large-scale networks similar to the Internet.

We carry out 1000 simulations of our model, each with a unique population and initial topology. As Tier-2 NSPs play during network formation, we measure the number of traffic flows and total traffic volume transiting each Tier-2 NSP i before and after it forms a peering relationship with another node j. We also measure the traffic T'_{ij} and T'_{ji} after L'_{ij} has been formed. Our objective is to determine the changes in traffic volume of i with each new peering link and the fraction of peering relationships which fall in the category of "premature acceptance" as described in section 4.2.1.

We find that only 10% peering links fall in the category of "premature acceptance" by one of the peers, i.e., a posteriori analysis of the traffic on the peering link reveals that the traffic ratio is out of bounds for one of the peers. All peering links in this category are those which are formed between Tier-2 NSPs. If one of the peers has a major content provider and the other has a major access ISP as its customer, the traffic on link is likely to be asymmetric. However, such asymmetries are not detected during peer evaluation phase as players only take into account local traffic and ignore customer traffic.

Figure 5 shows the relative difference between the number of traffic flows and traffic volume before and after each peering link is formed by each Tier-2 NSP. We find that approximately 85% peering links result in an overall increase in the number of traffic flows and traffic volume transiting the player. However, because of the skewed nature of the traffic distribution, the addition or removal of a few traffic flows carrying traffic for major content or access providers can significantly affect the traffic volume transiting a node. Furthermore, changes in traffic volume have a direct bearing on the utility of the players.

Our analysis shows that the peering links contributing to a significant increase ($\geq 50\%$) in the number of traffic flows are the ones which are formed between two Tier-2 NSPs. These players have large number of customers which often find that a peering link between their providers offers them a shorter path to one another. Whereas, the most significant increase in traffic volume ($\geq 50\%$) arises from peering directly with major content and access providers. Interestingly, we find that the Tier-2 NSPs undergoing significant losses in traffic volume with peering are the ones which have major content or access providers as their customers. These large nodes are often multihomed to Tier-1 nodes providing them with short paths to the entire network. Any peering link formed by their Tier-2 providers that increases their path length by even a single hop can lead these large nodes to divert their traffic away from the Tier-2 provider.

These results imply that the scope of analysis for peering decisions should not be limited to local traffic only; instead it should also incorporate customer traffic data as much as possible. Furthermore, the identification and evaluation of peers using NetFlow is inherently inaccurate for Tier-2 NSPs and may result in premature rejection of peers, premature acceptance of peers which do not qualify and lead to conflicts, and even a negative impact

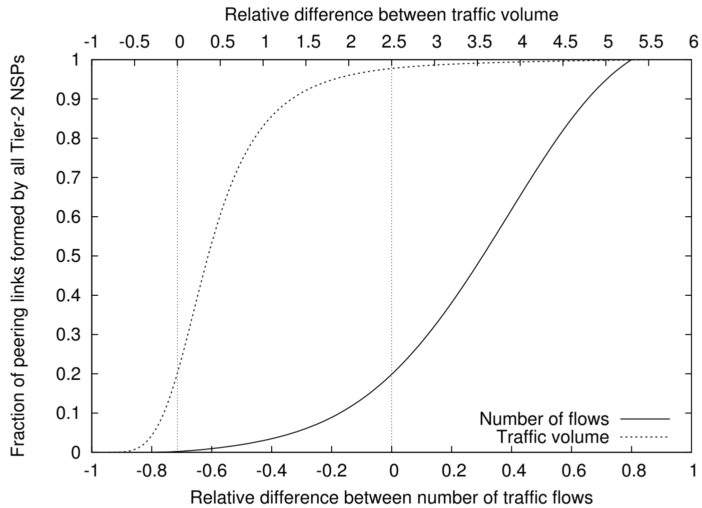


Figure 5: Relative difference between number of traffic flows and volume before and after formation of a peering link

on utility.

4.3 *Economic Uncertainty in Peering*

In this section, we evaluate the second obstruction to optimal peering choices, i.e., a complex transit and peering prices structure that has evolved as transit providers and IXPs try to lure customers towards themselves.

4.3.1 Analysis for Settlement-free Peering

Over a period of time simple rules-of-thumb have come in usage to decide the mode of traffic exchange, e.g., move as much traffic as possible to a settlement-free peering link to cut down costs.

Figure 8 shows that peering costs are much lower than transit costs for the same traffic volume. Hence, the first instinct of many operators is to offload as much traffic as possible on peering links. However, the analysis has to be carried out in totality because diverting traffic from a transit link to a peering link may also affect the transit price per unit traffic. We illustrate this complexity by the following example. Consider a Tier-2 NSP i with 10

Gbps upstream transit traffic. It would incur a monthly cost of \$10,000 in transit payments. Let us assume that i can divert as much as 50% of its traffic onto peering links at an IXP. With 5 Gbps transit and peering traffic each, the transit cost of i becomes \$20,000 with an additional IXP cost of \$1700, thus resulting in a total cost of \$21,700 - an increase of \$11,700 over the original cost. The transit cost increased dramatically because of the complex economies-of-scale engineered in the pricing structure.

Effect on utility components

The general notion is that settlement-free peering increases utility by lowering transit costs. In section 4.2 we showed that peering can change the traffic volume transiting through a network. We show that possible traffic variation and the complex pricing structure can affect all components of utility under settlement-free peering: transit and peering costs and transit revenues.

Computational Results: We simulate 1000 instances, each with a unique population and initial topology, of our model. In each simulation, we record the utility and its components of each Tier-2 NSP before and after it has committed its peering decisions.

Our analysis shows that 10% of players actually have their utility decreased after peering. Furthermore, 1.5% of players have their utility decreased by more than 50%.

Figure 6 shows the change in transit revenue, transit costs and cumulative costs (sum of transit and peering costs) for players which undergo a decrease in utility. Although transit costs decrease for 80% of such players, yet the cumulative costs increase for 75% of them. Similarly, 34% of such players also face a loss in revenue as their customers divert traffic away from them after peering. Figure 7 shows similar analysis for players which increase their utility. Although cumulative costs increase for 50% of such players, yet they are able to register a net benefit through an increase in transit revenue as well. Thus, NSPs require more careful analysis of their utility before committing to large-scale peering.

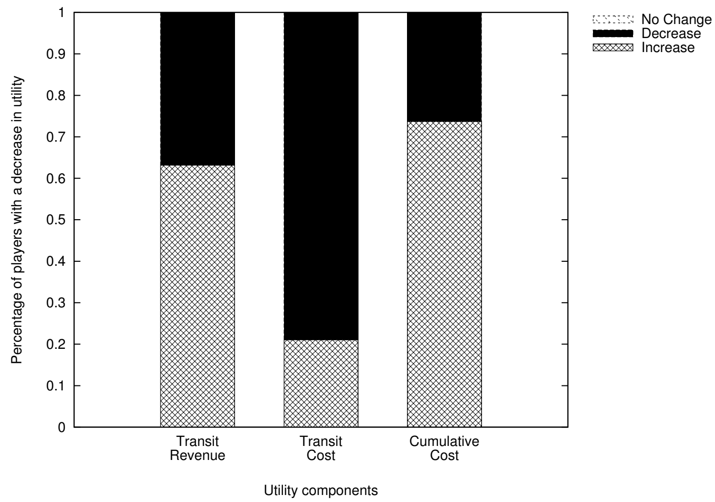


Figure 6: Effect on utility components of Tier-2 NSPs with a decrease in utility after peering

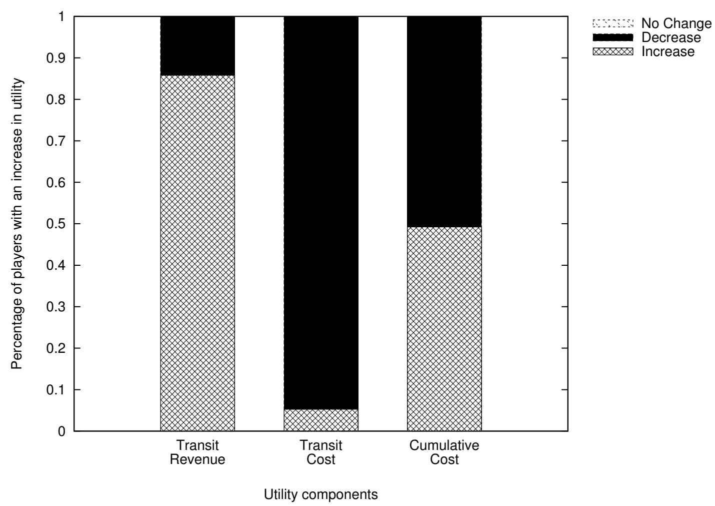


Figure 7: Effect on utility components of Tier-2 NSPs with an increase in utility after peering

4.3.2 Analysis for Paid-peering

Although paid-peering has been getting a lot of attention recently, our simulations show that only a small fraction of NSPs are able to form paid peering links. We attribute limited adoption of paid peering to the following two reasons:

1. On average, 70% potential peers of a Tier-2 NSP i satisfy its traffic ratio requirements. Hence, i cannot ask them to be its paid peering customers.

2. In approximately 50% of the paid-peering evaluations, on average, where a potential peer j does not satisfy the traffic ratio of i, cost-benefit-analysis by j reveals that a mix of paid-peering and transit is more costly for j than its transit alone. Hence j refuses to be a paid peer of i.

Similar to settlement-free peering, the cumulative costs of paid-peering and transit mix can exceed the costs under transit alone. Figure 9 shows the total cost of traffic exchange versus the fraction of total traffic that is diverted on a paid peering link. We find that although paid-peering is priced at half the transit price, yet adoption of paid peering favors only a small class of Tier-2 NSPs. We find that Tier-2 NSPs with the following characteristics generally benefit from being paid-peering providers:

1. Tier-2 NSPs with very large local traffic volume ($\geq 500Gbps$). Their large traffic volumes ensure that they can continue to use the same transit prices even after diverting a fraction of their traffic from transit to paid-peering links.

2. Tier-2 NSPs whose local inbound traffic is much greater than local outbound traffic which makes them attractive paid-peering providers.

3. Tier-2 NSPs which do not have large content providers as customers. Although having large content providers as customers is beneficial for transit revenue, yet large outbound traffic makes such transit providers unattractive for paid peering.

Furthermore, we find that having a large number of smaller customers does not turn a Tier-2 NSP into an attractive paid-peering provider because having a large number of small generally produces balanced traffic ratios which favor settlement-free relationships.

These results imply that the scope of economic analysis for peering decisions should not be limited to reduction of transit costs only; instead it should also incorporate the effect of peering on customer revenue and transit costs as much as possible.

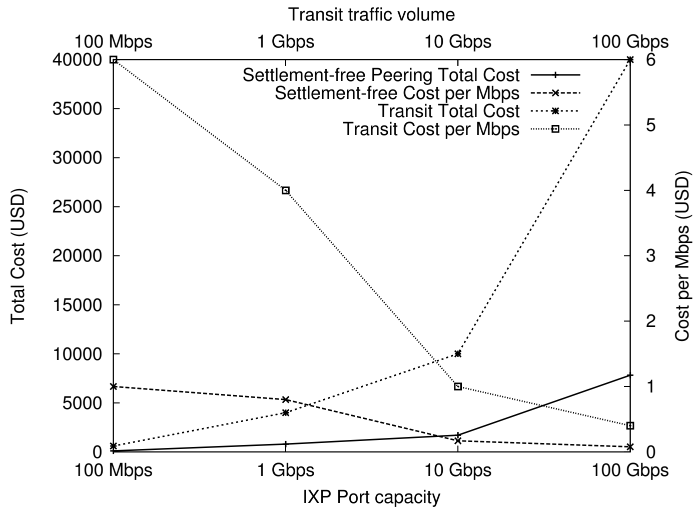


Figure 8: Peering Cost vs. Transit Cost (monthly recurring)

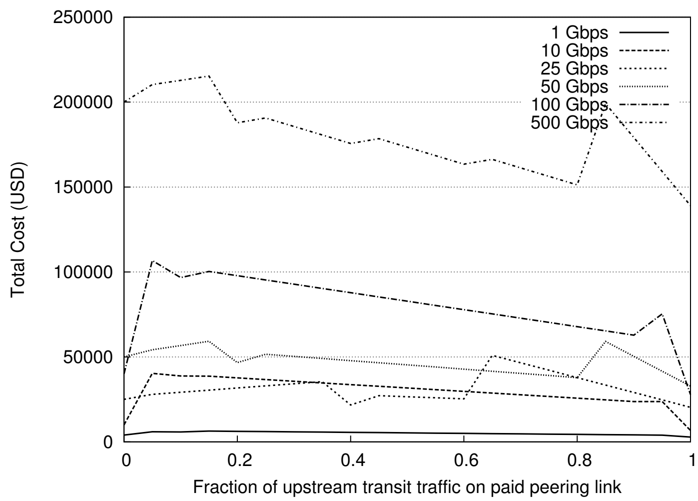


Figure 9: Transit + Paid-Peering Cost vs. Fraction of transit traffic on a paid peering link (monthly recurring)

4.4 Complexity of Determining the Optimal Set of Peers

In this section, we evaluate if the myopic one-by-one analysis policy for peers described in section 1.2 is sufficient to get an optimal utility. Furthermore, we evaluate if it is feasible for an NSP to do a combinatorial optimization of its peering set instead of doing the one-by-one. For simplicity, we assume that NetFlow is able to provide accurate estimates of traffic that would be exchanged over any proposed link[3].

4.4.1 Interdependence of Peering Links

We illustrate this complexity through a simple network in figure 10 where ASes i, j and k are co-located with one another. Let i and j be two Tier-2 NSPs where i actively seeks peers and j and k only respond to peering requests. Since k is a stub, it uses Open peering. Furthermore let $T_{ik} \gg T_{ij}$. i has a choice of four distinct *peering configurations* shown in the figure. Each configuration may incur different transit, paid-peering and IXP costs and yield different paid-peering revenues. i evaluates its utility under each configuration, beginning with configuration A shown in figure 10a.

In configuration A, i has no peers and incurs a steep transit cost for exchanging traffic through its upstream transit providers. Let π_i^A be the utility of i under configuration A.

In configuration B, shown in figure 10b, i evaluates peering with j. T_{ik} and T_{ki} will be routed through j under this configuration. Let

$$\frac{T_{ij} + T_{ik}}{T_{ji} + T_{ki}} > \sigma \tag{11}$$

Thus, j refuses settlement-free peering to i and instead offers i to become its paid-peering customer. i carries out cost-benefit-analysis for L_{ij}^p. Let i determine that $\pi_i^A > \pi_i^B$. Hence, i refuses to become paid-peering customer of j.

In configuration C, shown in figure 10c, i determines that

$$\frac{T_{ki}}{T_{ik}} \leq \sigma \tag{12}$$

Since k uses Open peering policy, it accepts peering with i. Let $\pi_i^C < \pi_i^A$ since i saves on transit costs under configuration C and peering costs are generally lower than transit costs. Hence, i peers with j.

[3] Suboptimal peering decisions would be even worse in the presence of limited information.

Let i re-evaluate j in configuration D, shown in figure 10d. Now that traffic $T_{ik} + T_{ki}$ will not be routed over L_{ij}^p, the ratio computation in expression 11 no longer holds. Upon re-evaluation, j finds that:

$$\frac{T_{ij}}{T_{ji}} \leq \sigma \tag{13}$$

However, let i find that:

$$\frac{T_{ji}}{T_{ij}} > \sigma \tag{14}$$

Hence, i can acquire j as a paid-peering customer, increasing its utility. Thus, the evaluation of the four configurations reveals that:

$$\pi_i^B < \pi_i^A < \pi_i^C < \pi_i^D \tag{15}$$

Thus, i had to evaluate all possible combinations of peers to determine the optimal set of peers.

4.4.2 Infeasibility of Exhaustive Search

An NSP can use brute force approach to exhaustively search the space for all possible peer combinations, compute its utility for each combination and determine the one that gives it the optimal utility. Let K denote the number of peers and M the number of potential peers of i. Then the total number of combinations, Q, that i may need to evaluate is given by:

$$Q = \sum_{K=0}^{M} \binom{M}{K} \tag{16}$$

yielding a complexity of $O(2^M)$ for exhaustive search of all possible combinations of peers.

Our analysis shows that peering decisions may be intertwined with one another and hence the decision for one peer may affect the decisions for other peers. Furthermore, it is

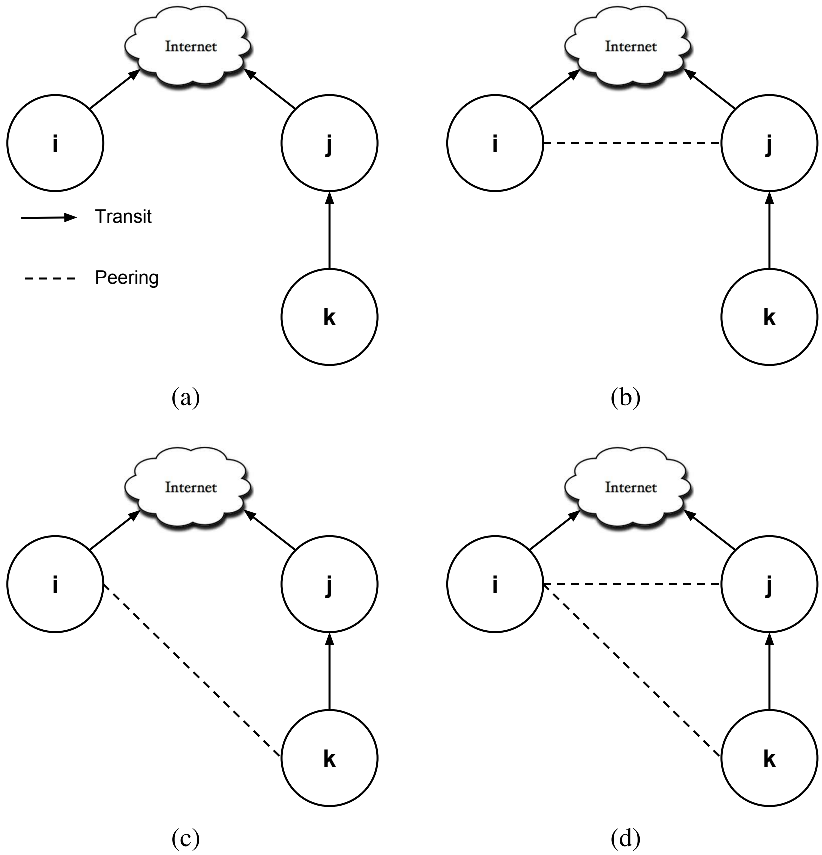


Figure 10: Peering interdependencies

infeasible even for a modest sized NSP, which is typically co-located with a large number of ASes at major IXPs, to compute the optimal set of peers through exhaustive search.

4.4.3 Intractability of Finding the Optimal Set of Peers

If peering with a set of ASes optimizes the utility of an AS x, then we define the set as the optimal set of peers for x. For the special case of public peering we can show that finding the optimal set of peers from a given set of candidate peers is NP-complete. In order to evaluate any subset of candidate peers, x has to compute each utility component (transit costs, peering costs, transit revenue) under that peering configuration. In order to minimize the peering costs, peering traffic flows have to be assigned to IXP ports such that the total cost of ports is minimized.

Let $\mathcal{T} = \{t_1, t_2, ..., t_n\}$ be the set of traffic flows traversing all its peering links ($t_m > 0$

Mbps). x has to assign all traffic flows to IXP ports such that the total cost of the ports is minimized. For simplicity, we assume that all IXP ports have the same capacity [4]. Given an IXP port p of capacity C and the set of traffic flows $\mathcal{T}$, we have to find an integer number of ports M and a $M - partition$ $p_1 \bigcup p_2 ... \bigcup p_M$ of the set {1,2,...n} such that

$$\sum_{i \in p_k} t_i \leq C$$

$\forall k = 1, 2, ..., M$. A solution is optimal if it has minimal M. The M-value for an optimal solution is denoted **OPT** is shown below:

minimize

$$B = \sum_{i=1}^{n} y_i$$

subject to: $\sum_{j=1}^{n} t_j x_{ij} \leq C y_i, \forall i \in \{1, \ldots, n\}$

$\sum_{i=1}^{n} x_{ij} = 1, \forall j \in \{1, \ldots, n\}$

$y_i \in \{0, 1\}, \forall i \in \{1, \ldots, n\}$

$x_{ij} \in \{0, 1\}, \forall i \in \{1, \ldots, n\} \forall j \in \{1, \ldots, n\}$

where $y_i = 1$ if port i is used and $x_{ij} = 1$ if traffic flow t_j is put into port i.

We can easily reduce the well-known NP-complete problem Bin-Packing to the problem of assigning traffic flows to ports, by mapping the ports to bins and traffic flows to items in the Bin-Packing problem.

[4] In section 4.1 we showed that IXP ports can have distinct capacities and prices.

CHAPTER V

THE STATE OF THE INTERNET INTERDOMAIN PEERING ECOSYSTEM (AUGUST 2010 - AUGUST 2013)

Although most of society considers the Internet as a critical infrastructure by now, we still know surprisingly little about its dynamics and structure. Its opaqueness is due to both the complexity of network interactions and the proprietary treatment of many aspects of these interactions by commercial providers. One source of public data on some of these network interactions that has yet to be systematically mined by researchers is PeeringDB [14]. PeeringDB [14] is an online open database where the operators of Autonomous Systems (ASes) provide information about the networks, such as peering policies, traffic volumes and presence at various geographic locations. PeeringDB was established in 2004 to assist peering coordinators identifying potential peers and peering locations. Over the last 3 years it has grown by 74% from 1950 participants in August 2010 to 3392 in August 2013.

Networks registered in PeeringDB self-report their business type, yielding a data set that can be used directly or to validate other AS business-type inference algorithms [38, 43, 90]. Second, networks report the set of IXPs and private peering facilites at which they are present. Third, networks self-report their general peering policy (either "Open", "Selective", or "Restrictive") and approximate traffic levels. Data on these four AS properties (business type, peering presence, traffic volume, peering policy) can help parameterize models of interdomain interconnection economics and traffic flow ([29, **?**, 62, 34], among others). To the best of our knowledge, PeeringDB is the only centralized resource available to the research community that publishes such data.

In this chapter we undertake a study of PeeringDB data to investigate three questions.

First, since PeeringDB participation is voluntary, with no mechanism to verify the accuracy of reported information, we investigate whether the PeeringDB dataset is representative, correct, and current. We then explore PeeringDB data from the *network perspective*, focusing on the geographic expanse, traffic volume, address space and peering policies that networks advertise. Our goal is to discover correlations between these properties; the presence of strong correlations would allow us to estimate properties of networks that are otherwise difficult to obtain (e.g., approximate traffic levels) using a property we can estimate from publicly available data (e.g, size of advertised address space). Finally, we explore what historical snapshots of the PeeringDB database can tell us about the evolution of the Internet peering ecosytem.

We find that PeeringDB membership is representative of transit, content, and access provider populations, and that most networks keep their records current. The data less accurately reflects *IXP properties* such as member counts and their evolution over time, because many networks in developing regions do not participate in PeeringDB. We find strong correlations among different measures of network size – advertised address space (from BGP), traffic volume and geographic expanse (reported on PeeringdB), and between these size measures and the peering strategies that those networks use. The presence of such correlations allows us to estimate difficult-to-obtain network properties, such as traffic volume and peering policy, using parameters such as the BGP-advertised address space or geographic expanse that are easier to obtain. Using three years of historical PeeringDB snapshots, we observe the evolution of the peering ecosystem – geographic expansion by content, access, and transit networks that agrees with their published peering behavior, changes in traffic volume, and a shift towards more restrictive peering. Furthermore, we find widespread adoption of Open peering among transit providers, which is counterintuitive given that transit providers prefer other ASes as their customers instead of peers.

5.1 Datasets

In this chapter we analyze the latest (August 2013) snapshot from PeeringDB, which we refer to as the **Aug13-PDB** dataset. Participating networks can report a wide range of attributes that are stored as fields in its database record [14]; we use the following fields:

Business type of the network, which is one of *Network Service Provider (NSP)* , *Cable/DSL/Access Provider*, *Content Provider*, Enterprise, *EducationResearch*, or *Non-Profit*.

Approximate traffic volume that the network handles, which ranges from *0-20Mbps* to *1+Tbps*, in 14 distinct bins.

Peering strategy that the network uses: *Open*, *Selective*, or *Restrictive*. ASes advertising a *Restrictive* peering policy are generally not inclined towards peering. ASes advertising a *Selective* policy prescribe a set of criteria (overall traffic volume, traffic ratios, minimum number of geographic locations of overlap, etc.) that potential peers must meet. ASes advertising an *Open* policy are generally willing to peer with any co-located network.

The IXPs and private peering facilities where a network is present.

To examine whether PeeringDB participants are representative of the AS population, we construct an AS topology using BGP routing table dumps from Routeviews [12] and RIPE RIS [93] in the first week of August 2013. We use CAIDA's AS-relationship algorithm [81] to infer the number of customers of each AS. We use this BGP data to determine the size of the address space that each AS originates (removing double-counting due to ASes advertising overlapping prefixes). We classify ASes according to broad geographic regions using the RIR database (WHOIS) where the AS is registered: ARIN (North America), RIPE (Europe, Middle East, and the former USSR), APNIC (Asia/Pacific), AfriNIC (Africa), and LACNIC (Latin America). We refer to the dataset obtained from BGP and WHOIS information as the **Aug13-BGP** dataset.

Through private communication with the PeeringDB operators we found that they do not maintain historical snapshots of the PeeringDB data. However, they publish a nightly mysql dump of the entire database, which we have been archiving daily since July 2010.

To the best of our knowledge, this is the only resource of historical peering data available to the research community. We will make this data available publicly via CAIDA's data sharing portal [33].

5.2 *Representativeness and Usability of PeeringDB data*

Given that PeeringDB runs on a volunteer basis, a key question is whether PeeringDB participants are representative of the general AS population, and whether the data is up-to-date and correct.

5.2.1 Business type representation of PeeringDB

We first study whether the business type of PeeringDB participants is representative of the entire AS population. The **Aug13-PDB** dataset contains 3392 ASes (7.5% of the number in **Aug13-BGP**), of which 31% are *Network Service Providers* (NSP) (Transit Providers), 25% *Content Providers*, 33% *Access Providers*, 4% *Enterprise Networks*, 4% *Educational/Research*, and 3% are *Non-profit organizations*. The **Aug13-BGP** dataset contained 45074 ASes, of which 4.5% were *Transit providers*, 4.5% *Content/Access/Hosting providers*, and 91% were *Enterprise Customers* according to our scheme for classifying ASes into business types [38]. Based on this public BGP data, enterprise customers are under-represented in PeeringDB as compared to transit, content and access networks.

To determine if the largest transit networks are present in PeeringDB, we use CAIDA's AS-rank, which ranks transit providers according to the number of ASes present in the provider's customer cone [81]. We find that 93% of the top-100, 80% of the top-200 and 74% of the top-300 ASes from AS-rank were present in the **Aug13-PDB** dataset, including all known Tier-1 [6] and major Tier-2 ASes [7]. To determine whether popular content providers are present in PeeringDB, we used Alexa's ranking of major content sites in August 2013 [2] to find the ASes that host the most popular websites. 59% of ASes hosting the top-100, 39% of ASes hosting the top-500 and 38% of ASes hosting the top-1000 websites were present in **Aug13-PDB**. To determine whether popular access providers are present in PeeringDB, we crawled the tracker for the popular torrent site The Pirate Bay [11] over two weeks in July 2013, and obtained a list of IP addresses that connected to the tracker. We then mapped those IP addreses to ASes, and ranked ASes by the number of BitTorrent clients. We find that 54% of the top-100 ASes in terms of host count, 52% of the top-200, and 47% of the top-300 ASes were present in *Aug13-PDB*.

Limitations of AS representation in PeeringDB: Given that the objective of PeeringDB is to assist peering coordinators, it is likely to draw the attention of only that section of the network operator community that is interested in peering. Hence, we can expect organizations whose primary business is not Internet connectivity, e.g., education/research, retail enterprises, etc., networks with small traffic volumes, limited resources, small geographic footprint, to not appear in PeeringDB. Finally, some networks may not be willing to share information about themselves due to competitive reasons. This is evident as there were 8724 registered users in the **Aug13-PDB** dataset but only 3392 ASes that volunteered any information about themselves.

5.2.2 Geographical representation of PeeringDB

Our next question is whether the geographic distribution of PeeringDB participants matches that of all ASes seen in BGP. To answer this question we used WHOIS information to determine the RIR that each AS in peeringDB is registered in, and we compared that with the distribution for all ASes. The first two columns of Table 3 show the fraction of ASes in the **Aug13-PDB** and **Aug13-BGP** datasets associated with each registry. The APNIC, LACNIC, and AFRINIC registries have almost the same representation in the **Aug13-PDB** and **Aug13-BGP** datasets. RIPE, however, is over-represented and ARIN is under-represented in **Aug13-PDB**. Since PeeringDB membership is not representative of the entire AS population (most of which are stub networks [38]), we isolate the geographic distribution of *non-stub* networks in the two rightmost columns of Table 3. For this non-stub population,

Table 3: Geographical distribution of ASes in the **Aug13-PDB** and **Aug13-BGP** datasets. While the overall PeeringDB population is biased towards RIPE, the PeeringDB non-stub population is geographicly representative of the entire Internet.

Registry	**Aug13-PDB** All (%)	**BGP** All (%)	**Aug13-PDB** Non-stubs (%)	**BGP** Non-stubs (%)
ARIN	25.1	34.9	24.0	26.8
RIPE	53.2	44.2	53.6	49.8
APNIC	13.4	12.3	15.3	13.7
LACNIC	4.9	6.2	5.1	7.4
AFRINIC	1.7	1.5	1.7	2.1

the representation bias towards RIPE (over ARIN) is much lower; the geographic characteristics of non-stub PeeringDB participants are thus similar to those of the larger Internet.

5.2.3 Freshness of PeeringDB records

Using the *last updated* field in PeeringDB records in the Aug 1, 2013 snapshot, we find that the median time since the last update was between 10-14 months for NSPs, Cable/DSL/Access providers and Content providers, and 17 months for Enterprise networks. When we considered the top-20 NSPs, top-20 Content and top-20 Access providers (ranked according to their advertised traffic volume), 70% of this set had updated their peeringDB records in the month preceding August 1, 2013. PeeringDB records thus appear to be reasonably current. PeeringDB does not incorporate topology data, which is more susceptible to frequent variation. We do not expect peering policies, geographic co-location and traffic profiles to change frequently.

5.2.4 Correctness of data reported in PeeringDB

Snijders [100] recently found that PeeringDB data was 99% accurate with respect to network presence at IXPs, i.e., 99% of the instances where a network reported presence at an IXP were true. To check the consistency of peering policies that networks report on PeeringDB and on their webpages, we obtained the peering policy URLs of 50 networks in PeeringDB, and compared the policy seen on their URL with the policy mentioned in the PeeringDB record. In each case, the peering policy listed on PeeringDB (Open, Selective or Restrictive) matched the peering policy at that network's policy URL. Verifying other self-reported network properties such as traffic volume is difficult; however, we are currently developing a method to compare a network's advertised peering policy with its peering behavior at various IXP route servers.

We investigated whether we could use PeeringDB to infer a specific *IXP property* – the number of members present at that IXP. For each of the top-20 IXPs for which we could find member lists online, we calculated a ratio of the number of members of the IXP inferred from PeeringDB to the number of members obtained from the IXP's webpage. If a network does not participate in PeeringDB but is present at an IXP, then that network does not appear in the member list created from PeeringDB. Consequently, for each of the top-20 IXPs, this ratio is less than 1; the median is 0.8. For some IXPs this ratio is close to 1 , e.g, LINX Extreme LAN (0.99), LINX Juniper LAN (0.98), Seattle Internet Exchange (0.98); these IXPs encourage their members to join PeeringDB. For many IXPs the ratio is small, especially in developing regions, e.g., Moscow IX (0.25), PTT Sao Paolo (0.32) and Hong Kong IX (0.62). We conclude that IXP member counts from PeeringDB are a lower bound on the number of networks present at the IXP; they are not complete membership lists. Consequently, PeeringDB should not be used to estimate the size (in terms of member count), or the diversity of the participants at an IXP, unless we first verify that the member list generated from PeeringDB is close to that obtained from the IXP iteself.

5.3 Properties of participants

We explore the use of PeeringDB to infer properties of networks that are difficult to obtain from other sources. We focus on three measures of a *network's size* – geographic expanse (the number of IXPs and private peering facilities), advertised traffic volume, and BGP-advertised IPv4 address space. Networks self-report the first two properties in PeeringDB; we obtain the size of the IPv4 address space from publicly available BGP data. Metrics of the size and geographic expanse of networks are important for developing, parametering, and evaluating models of interdomain economics and interconnection [29, **?**, 62, 34]. Moreover, the presence of strong correlations between these properties would enable us to estimate a network property that is difficult to measure (e.g., traffic volume) using a property that is more readily available (advertised address space, or number of peering locations).

Geographical expanse: Figure 11 shows the distribution of the number of IXPs and private peering facilities where participating networks (classified according to their self-reported business type) are present. Unsurprisingly, the self-reported data indicates that NSPs tend to have presence at more IXPs (median=2 and 90th percentile=8) and private peering facilities (median=2 and 90th percentile=9) than other network types. The median number of IXPs for Enterprise, Content and Access networks is a single IXP, while the 90th percentile is 2 for Enterprise networks and 4 for Content and Access networks. More surprising is that the presence of Enterprise networks at private peering facilities is comparable to that of content and access providers; in each category, the median is a single facility and 90th percentile is 5 facilities. Conventional wisdom suggests that enterprise networks are usually stubs at the edge of the network that do not engage in widespread peering. While the sample of Enterprise networks in PeeringDB is small (only 120 networks), and contains networks such as Amazon and Websense Hosted Security that peer at many locations, it suggests a trend toward richer peering at the periphery of the Internet.

Relation between geographic expanse and traffic volume: We examine the correlation between the geographic expanse of a network (the number of IXPs and private peering facilities) and the advertised traffic volume of that network. Figure 12 bins the total number of locations where a network is present, and shows the distribution of the traffic volume of networks in each bin. In general, the number of locations where a network is present at positively correlates with its advertised traffic volume. The fraction of networks advertising large traffic volumes (100-1000Gbps and 1Tbps+) increases with the total number of

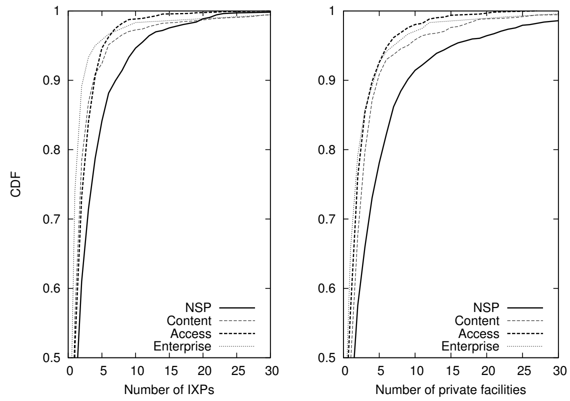


Figure 11: Distribution of the number of IXPs and private peering facilities at whcih PeeringDB participants are present. NSPs are generally present at the largest number of IXPs and private peering facilities. Enterprise networks are similar to content and access in geographic expanse.

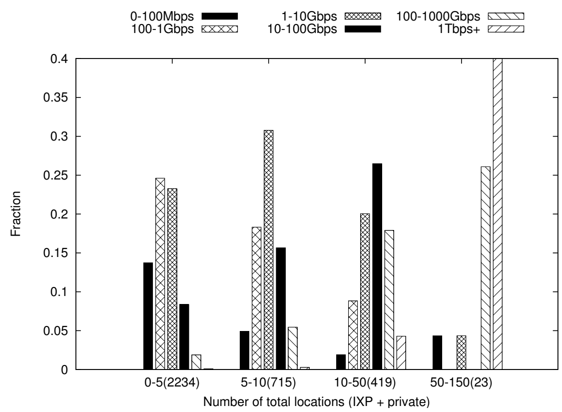


Figure 12: Number of locations at which a network is present vs. self-reported traffic volume. Networks present at more locations are more likely to advertise larger traffic volumes. Total number of networks in each category given in paranthesis.

locations. The number of peering locations of a network is usually easier to discover than its traffic volume, and the correlation between these factors suggests that we may be able to roughly estimate the latter based on the former.

Relation between traffic volume and advertised address space: Figure 13 shows the median, 10th and 90th percentiles of the advertised address space size for each advertised traffic volume for different classes of networks. Access and enterprise networks have the largest median advertised address space for each traffic volume, with strong correlation (correlation coefficient 0.91), while content providers have the smallest median advertised

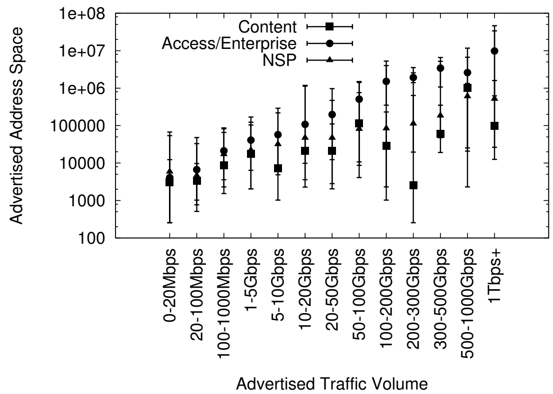


Figure 13: Reported traffic volume of a network and its advertised address space size. Networks advertising more address space also report higher traffic volumes. Access/Enterprise networks advertise more address space per unit of traffic than transit and content networks.

address space for each traffic volume with weaker correlation (correlation coefficient 0.56). NSPs show the strongest correlation coefficient (0.95) betwen advertised traffic volume and advertised address space, but lower median values than access and enterprise networks. These trends match what we expect from these business types. Access and enterprise networks serve end-users, and their traffic volume typically increases with the size of their advertised address space; in contrast, content providers do not require much address space to serve content. Since a network's BGP-advertised address space is computable from public data, its strong correlation (for access, enterprise and transit networks) with traffic volume suggests that we may be able to use BGP data to estimate the approximate traffic volume of other networks on the Internet.

Changes in the traffic volume of participating networks: Given that reported global traffic levels in the Internet continue to increase rapidly [32], we expect that most networks should advertise larger traffic volumes over time. For PeeringDB snapshots between August 2010 and 2013, 35% of access providers, 42% of content providers, and 29% of transit networks reported a *decrease* in their traffic volume. We do not know whether this decrease is due to a loss of customers, or consolidation in the content delivery and access markets [66]. Another plausible hypothesis is that networks initially advertise inflated traffic volumes to peer with large networks. Over time, however, networks are able to determine the actual traffic volumes being exchanged with their peers. Hence, networks advertising inflated traffic volumes may realize that doing so only leads to unstable peering relationships and drives away peers with whom they could have formed stable links. Therefore, they report figures closer to reality. Correlating observed changes in traffic volume with publicly available financial information about revenues and incomes could help identify cases where traffic volume changes are due to factors such as loss of market share (as opposed to changes due to more truthful reporting). Such *actual changes* of traffic volume may help researchers validate models that relate traffic flow to economics and strategic decisions of network.

Geographical expansion by networks: Researchers have studied the geographic expansion of networks, and the resulting *flattening* of the Internet topology [53, **?**]. Historical peeringDB snapshots allow us to estimate the geographic expansion by participating networks. Of 2,525 networks present in both Aug 2010 and Aug 2013, 25% increased their presence at IXPs, and 25% increased their presence at private peering facilities. When classified by business type, 33% of NSPs present in both snapshots increased their presence at IXPs and 37% did so at private peering facilities. The increase at peering locations was 24% and 31% for Content providers, and 28% and 31% for Cable/Access/DSL providers. The following case studies from each business type illuminate the changing structure of the ecosystem.

Content providers: From 2010 to 2013, Google increased its peering presence from 57 to 72 IXPs and from 58 to 77 private facilities. Akamai's presence at private peering facilities is almost constant (35 in 2010 to 36 in 2013), while its presence at IXPs increased from 47 to 74. Limelight Networks' presence at IXPs remained constant at 42, while it expanded its presence at private facilities from 55 to 65. These observations are consistent with well-documented peering policies of these networks [55, 20], i.e., engage in Open peering at IXPs for low-traffic peers and private peering for high-traffic peers. In contrast, Limelight Networks advertises a Selective peering policy requiring a minimum of 1Gbps of traffic [71], implying that it prefers private peering with qualifying networks. The geographic expansion of Netflix follows its growth as a major source of Internet traffic. In 2010, Netflix was present at one IXP and one private peering facility; in 2013, it is present at 21 IXPs and 27 private peering facilities.

Access Providers: Major access providers, e.g., Comcast, Time Warner Cable, Vodafone and ClaraNet announce Selective or Restrictive peering policies. Vodafone and Claranet *decreased* their IXP presence between 2010 and 2013 (from 7 to 5 and 15 to 11, respectively), while Comcast did not report presence at any IXPs since 2010 (and was present at 17 private facilities in 2013). Time Warner Cable reduced its private peering locations from 12 to 10 and added a single IXP between 2010 and 2013.

Transit Providers: Large transit providers, e.g., AT&T, Level3, Global Crossing (Now Level3), TiNet, TeliaSonera, Deutsche Telekom and TATA announce Restrictive or Selective policies. AT&T and Level3 are not present at any IXP or private peering facility; presumably they prefer to peer at their own facilities. Tinet, Deutsche Telekom, TATA, and TeliaSonera have all decreased their presence at IXPs and increased their private peering count from 2010 to 2013. Hurricane Electric is an interesting exception; it advertises an Open peering policy, and has increased its IXP and private peering count (from 43 to 68 and 27 to 58, respectively).

Network presence at multi-IXP cities: PeeringDB lists 59 cities with more than one IXP. For networks in multi-IXP cities, peering at multiple IXPs could increase the diversity of peering partners and resiliency of interconnection. For each multi-IXP city with 4 or more IXPs, Figure 14 shows the fraction of networks present in that city that connect to a given number of IXPs. Perhaps unsurprisingly, there are significant differences between cities; in Chicago, Montreal, and Singapore, close to 90% of the networks are present at a single IXP in that city. London and Paris, on the other hand, present the opposite case, where 40% and 35% of participants respectively are present at 2 IXPs. Delving into why networks in

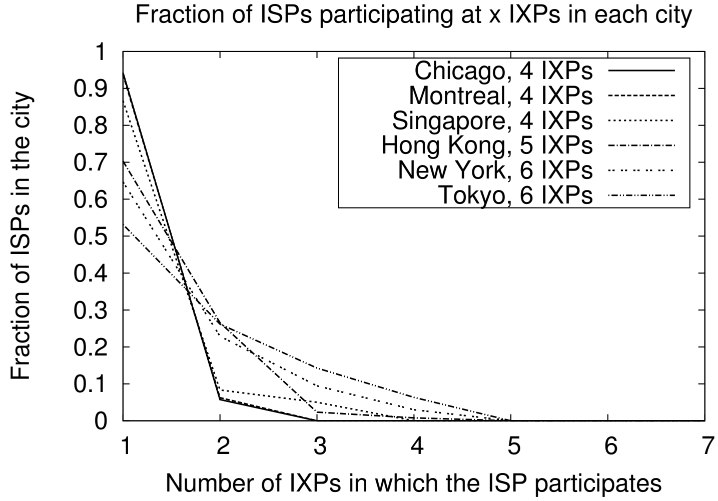


Figure 14: For each multi-IXP city with 4 or more IXPs, the fraction of networks that are present at different numbers of IXPs.

different multi-IXP cities peer differently involves looking into the size, business model, and diversity of the participant mix at these different IXPs, which we plan to do in future work.

5.4 Advertised Peering Policies

Network presence at IXPs is a measure of the *ability* of networks to peer with other co-located networks, but says nothing about their *willingness* to do so. Peering policies advertised in PeeringDB can serve as a coarse measure of peering openness. We emphasize that a network is under no obligation to follow its announced peering policy. At the same time it is unlikely that networks can derive any advantage by advertising a completely different peering policy than what they follow in practice. For example, a network implementing Open policy would only drive potential peers away by advertising a Selective policy. Similarly, a network implementing Selective policy while advertising Open will form many unstable peering links as most links will fail to qualify its satisfy its peering constraints. Nevertheless, the peering policies in PeeringDB should be viewed as a coarse measure of peering openness, as many networks also require that their peers follow additional constraints, e.g., co-location at more than one IXP, traffic volume exchanged between peers,

Table 4: Peering strategy distribution by network type. Open peering is the dominant peering strategy irrespective of business type.

Type	Total	Open (%)	Selective (%)	Restrictive (%)
NSP	1064	66.7	28.7	4.5
Content	843	83.9	14.4	1.5
Access	1122	79.1	18.5	2.3
Enterprise	120	65.0	27.5	7.5
Edu/Research	133	69.1	28.5	2.2
Non-profit	108	81.4	14.8	3.7

24/7 operator support, etc. Another reason for deviation from advertised peering policies is due to the complexities of implementing import/export filters to enforce these policies when a network connects to an IXP's route server. Giotsas et al. [54] found that some networks advertising a Selective peering policy in PeeringDB were actually engaging in open peering at some IXPs, due to the complexity of setting fine-grained import/export policies at the corresponding route server.

Of the 3392 ASes in the **Aug13-PDB** dataset, 76% use *Open* peering, 21% use *Selective*, and 3% use *Restrictive*. We examine whether this preference for *Open* peering depends on other properties of these networks such as their business type, or the measures of network size (geographic expanse, approximate traffic volume).

Peering strategy distribution by business type: Table 4 shows the fraction of networks in each business type that advertise *Open*, *Selective* and *Restrictive* peering. Interestingly, the peering strategy distribution does not depend significantly on the AS business type. Between 65% to 84% of ASes from each business type advertise an *Open* peering strategy. The popularity of Open peering is counterintuitive, especially for transit providers, who could mostly use *Selective* or *Restrictive* peering to increase their customer base and transit revenues. The trend towards *Open* peering is not limited to small transit providers; 32% of NSPs with traffic volume greater than 100 Gbps, 43% of providers with traffic volume between 50 and 100 Gbps, and 56% of providers that advertise a global scope use *Open* peering.

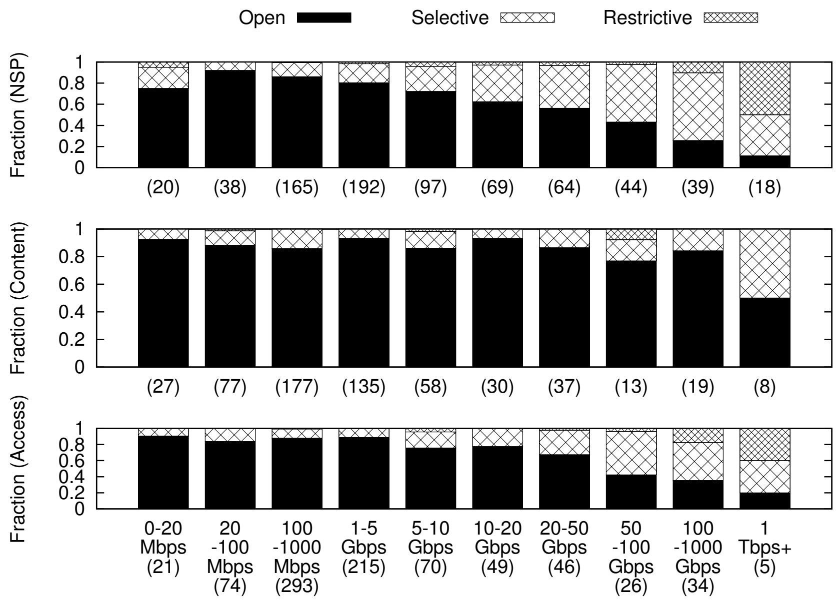


Figure 15: Peering strategy distribution of transit, content, and access providers – classification by traffic volume. Peering openness of transit and access networks is negatively correlated with geographic expanse. There is no such correlation for content providers.

Peering strategy distribution by traffic volume: Figure 15 shows the peering strategy distribution for NSPs, content providers, and access providers that advertise a given traffic volume. For NSPs and access providers the preference for *Open* peering gradually decreases as the AS's traffic volume increases. Low volume NSPs and access providers show a strong preference for *Open* peering; 80% of 415 NSPs and 87% of 603 access providers advertising traffic volume less than 5Gbps announce *Open* peering policy. On the other hand, only 1 out of 5 NSPs and 2 out of 18 access providers advertising more than 1 Tbps of traffic declare an *Open* peering policy. Content providers have a weaker relation between traffic volume and peering policy; 88% of 573 content providers with less than 1Tbps of traffic announce *Open* peering. Of 8 content providers with more than 1Tbps of traffic, 4 announce *Open* peering, and none announce *Restrictive* peering.

Peering strategy distribution – joint classification by traffic volume and number of customers: Transit providers (and also to some extent access providers, e.g. Comcast), rely on transit customers as a source of revenue. For these providers, peering openly could

Table 5: Peering strategy distribution of transit and access providers – joint classification by number of transit customers and traffic volume. Transit providers with low traffic and few customers are most likely to adopt Open peering; providers with large traffic and many customers are least likely.

Class	Total	Open (%)	Selective (%)	Restrictive(%)
Class-1 (ST+SC)	891	84.8	14.0	1.1
Class-2 (ST+LC)	19	57.9	36.8	5.3
Class-3 (LT+SC)	310	74.5	21.0	4.5
Class-4 (LT+LC)	344	46.8	45.3	7.6

mean losing revenue-generating customers. We use traffic volume and size of customer base to consider four classes of ASes:

Class-1: Small traffic volume, small number of customers (ST+SC)

Class-2: Small traffic volume, large number of customers (ST+LC)

Class-3: Large traffic volume, small number of customers (LT+SC)

Class-4: Large traffic volume, large number of customers (LT+LC)

Class-1 contains networks in the bottom 30% by traffic volume and bottom 30% by number of customers; Class-2 contains networks in the bottom 30% by traffic volume and top 70% by number of customers; other clases are defined similarly. Table 5 shows the peering strategy distribution for these four classes of ASes. Open peering is most common in Class-1 networks (85% of such ASes use Open peering) and is least popular for Class-4 ASes. However, 47% of even Class-4 ASes advertise *Open* peering. Using game-theoretic analysis and agent-based simulations, we have shown [75, 78] that transit providers can gravitate towards Open peering due to myopic decision making without coordination. Our results also showed that in a world with widespread Open peering, networks in Class-1 stand to gain, while networks in Class-4 stand to lose. The distribution of peering policies seen in the real world is consistent with our previous results [75, 78].

Peering strategy distribution by geographic expanse: Figure 16 shows the peering strategy distribution for NSPs, content and access providers as a function of their geographic

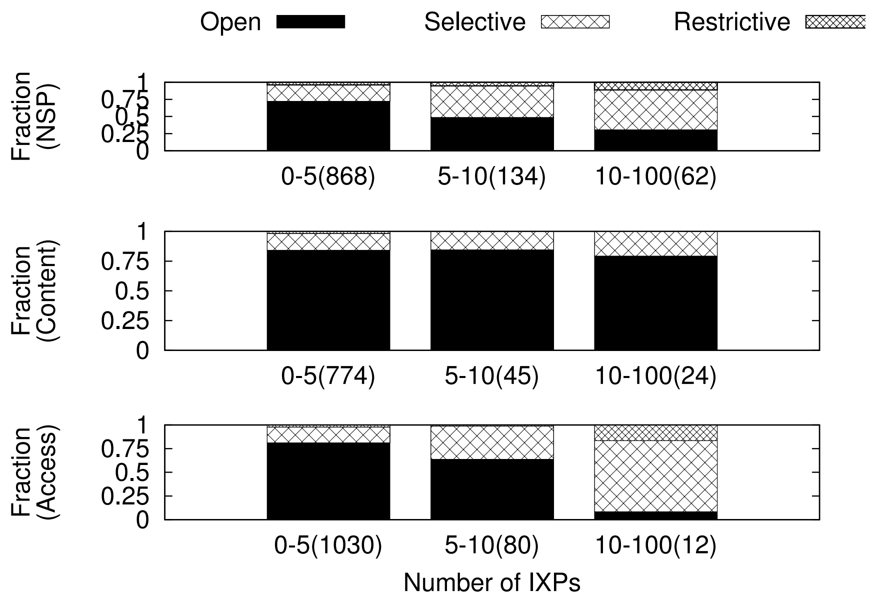


Figure 16: Peering strategy distribution of NSPs, Content, and Access providers by geographic expanse. Peering openness of NSPs and access networks is negatively correlated with traffic volume. We find no such correlation for content providers.

expanse (the number of IXPs at which they are present). Similar to the earlier classification by traffic volume, the peering strategy of content providers is largely independent of geographic expanse; these ASes mostly prefer Open peering independent of their size. The strategy distribution of NSPs and access networks strongly correlates with geographic expanse; the fraction of networks that announce an Open peering policy decreases with geographic expanse.

Strategy transitions: Between August 2010 and August 2013, 130 ASes in PeeringDB changed their peering strategy. Surprisingly, given the prevalence of Open peering, *most (70%) of networks that changed their peering strategy moved towards a more selective strategy*. When classified by self-reported business type, among these 130 ASes, 71% of access providers, 52% of content providers, and 80% of transit providers became more selective in their peering. When classified by traffic volume, 61% of networks with reported traffic less than 1Gbps, 81% of networks with 1-100Gbps and 83% of networks with more than 100Gbps became more selective in their peering policies. A plausible hypothesis for the change towards more selective peering is that these ASes became less profitable due to

Open peering, causing them to revert back. This shift may also be evidence of the "peering life cycle" [86], where networks initially advertise an Open peering policy and then become more selective with time.

CHAPTER VI

A PLAUSIBLE EXPLANATION FOR THE GRAVITATION TOWARDS OPEN PEERING BY INTERNET TRANSIT PROVIDERS

In this chapter we explore the peering behavior of transit providers and challenges the conventional notion that peering is always economically beneficial. We show that myopic and selfish adoption of peering strategies, and lack of coordination among transit providers can push transit providers towards Open peering. We also explain why transit providers may find it difficult to break out of the stable, but suboptimal, equilibria formed through Open peering.

The economic objective of peering is to reduce upstream transit costs. To a large degree, each AS X follows a *peering strategy* (or "peering policy"[1]) that is used to determine whether X will accept to peer with another AS Y. Even though they can vary widely in their details, most peering strategies can be grouped in three distinct classes: *Restrictive* (X peers only if necessary to avoid Internet partitioning; typically used by Tier-1 transit providers), *Selective* (X peers only with ASes that are comparable with X, a notion that we will define more precisely in Section 6.1), and *Open* (X is willing to peer with everyone, except its customers). The conventional wisdom is that transit providers use *Restrictive* or *Selective* peering, so that they can engage other ASes as their customers, thus increasing their transit revenues.

In the last few years, however, there is evidence that the Internet peering ecosystem is going through a major transformation from *more restrictive or selective* to *more open* interconnection. A recent study on peering interconnectivity at a large European Internet

[1] We use these two terms interchangeably.

Exchange Point (IXP) reveals a "rich peering fabric", with 67% of all possible peering relationships established at the IXP [19]. Such interconnectivity characteristics can only arise if a large percentage of ASes present at the IXP engages in Open peering. We have analyzed data from PeeringDB [14], an online database where peering coordinators provide information about their ASes. This data shows that most transit and access providers (70-80%) use the Open peering strategy. This is counterintuitive, especially for transit providers, because if they peer openly how can they attract new customers or keep their existing ones? More surprisingly, this trend is not limited to small transit providers. The PeeringDB dataset reveals that 36% of transit providers with traffic volume greater than 100 Gbps (e.g., Hurricane Electric), 37% of providers with traffic volume between 50 and 100 Gbps (e.g., WIND Telecomunicazioni S.P.A.) and 66% of providers with global scope (e.g., DeltaTelecom) use *Open* peering. Furthermore, the findings of a recent survey show that 99.5% of peering relationships are formed without formal analysis or agreements [10].

These observations on peering behavior raise some important questions: *Why do so many transit providers use Open peering? What are the underlying interconnectivity dynamics that influence their peering decisions? What does this attraction towards Open peering imply for the economic performance of transit providers? Is the inclination towards Open peering uniform across all categories of transit providers?* In the absence of any formal analysis for most peering agreements, the network-wide economic impact of peering on transit providers is not well understood. Furthermore, Internet providers, independent of their type, are secretive about their economic objectives and operational data. Hence, we cannot address the previously mentioned questions empirically. Instead, we rely on analytical and computational modeling for this purpose.

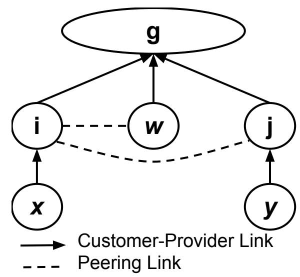


Figure 17: Network model with the fixed customer-provider links and some potential peering links

6.1 Analytical Results

6.1.1 Model Description

For the first part of this chapter, we use a much simplified version of our default model to ensure analytic tractability. The underlying basis of the model, however, remains the same.

The network model, shown in Figure 17, consists of five nodes: i, j, g, w, x and y. The nodes represent ASes that seek to optimize their utility by choosing the best peering strategy. w, x and y are *stubs* i.e., they do not have transit customers; they openly peer with any node that is willing to peer with them to minimize their transit costs. Node g is a tier-1 transit provider that uses the Restrictive peering policy, and so it does not peer with any other node. Its presence in the model is only to ensure that there is at least one path between any two nodes even if there are no peering links. i and j are *transit providers* that choose dynamically the peering strategy that maximizes their economic utility; these two nodes are the only players in the following repeated game.

Link formation and traffic routing: Nodes interconnect through one of two types of links: (a) customer-provider or transit links, and (b) peering links. Players i and j are customers of g; w, x and y are customers of g, i and j respectively. The customer-provider links remain fixed during the following game. However, peering links change as i and j adopt different peering policies, as explained later. We denote the link between any two nodes p and q by L_{pq}.

Only geographically co-located nodes can form links. The stubs w, x and y are not co-located. All other players are co-located and can form links with each other.

Traffic and routing: The traffic flow (Mbps) sent from node p to q is denoted by T_{pq}. We denote the total traffic exchanged between p and q by V_{pq},

$$V_{pq} = T_{pq} + T_{qp} \tag{17}$$

The total traffic of a node p, denoted by $\hat{V}_p$, is the sum of all traffic that p exchanges with other nodes.

Traffic follows the shortest path subject to two common policy constraints in the Internet [**?**]: "prefer customer over peer over provider links" and the "valley-free" routing property. If two nodes cannot exchange traffic directly over a peering link, they have to rely on an upstream transit provider to carry their traffic. For instance, in Figure 17, x exchanges traffic with w through its transit provider i; however, i exchanges traffic with w directly over their peering link instead of going through its transit provider g.

Peering strategies: Nodes form bilateral peering relationships based on their peering strategies. s_p denotes the peering policy of a node p. We consider the following three peering strategies, based on the policies that are announced at PeeringDB [14] and that are widely discussed at NANOG [8] and peering surveys [1]:

1. *Restrictive (R)*: Node p does not peer with any other node unless it is necessary to avoid network partitioning.

2. *Selective (S)*: Node p only peers with nodes that have similar (or larger) size than itself. We use the total traffic of a node as a proxy for its size. The rationale is that if a node q is much smaller than p, in terms of total traffic, then p would prefer to become a transit provider of q as opposed to a peer of q. $I_\sigma(p, q) = 1$ denotes that q satisfies the Selective peering constraint of p, stated as follows

$$I_\sigma(p, q) = 1 \iff \frac{\hat{V}_p}{\hat{V}_q} \leq \sigma \tag{18}$$

Table 6: Peers of i and j under different peering strategies

s_p	Peers of i		Peers of j	
	$I_\sigma(i,w)=1$	$I_\sigma(i,w)=0$	$I_\sigma(j,w)=1$	$I_\sigma(j,w)=0$
R	$\emptyset$	$\emptyset$	$\emptyset$	$\emptyset$
S	j, w	j	i, w	i
O	j, w, y	j, w, y	i, w, x	i, w, x

where σ denotes the Selective traffic ratio constraint ($\sigma \geq 1$), Otherwise, $I_\sigma(p,q) = 0$.

3. *Open (O)*: Node p peers with all co-located nodes except its existing customers.

Due to space constraints, we further assume the following two conditions so that the analysis focuses on the more interesting instances of the game. First, transit providers i and j satisfy each other's Selective peering constraint, i.e., $I_\sigma(i,j) = 1$ and $I_\sigma(j,i) = 1$ for the given value of σ, and so they always peer with each other. If this was not true, the providers i and j would be attracted to Open peering even more. Second, the traffic of stubs x and y are such that $I_\sigma(i,y) = 0$ and $I_\sigma(j,x) = 0$, i.e., they do not qualify to become peers of j and i, respectively. If this was not true, a provider would simply use Selective peering if w qualifies to become its peer, and Open otherwise. Recall that stubs, w, x and y peer openly with any player willing to peer with them.

Costs and revenues: Each provider v charges its transit customers a price of P_v \$/Mbps. For instance, if player i exchanges traffic $\mathcal{V}$ with its provider g, i incurs a transit cost[2] C_i^T,

$$C_i^T = P_g \times \mathcal{V} \tag{19}$$

The transit revenue of i, denoted by R_i, is the transit cost incurred by its (only) customer x.

Peering also incurs a cost. If $\mathcal{V}'$ is the total peering traffic of player i, its peering cost is given by:

$$C_i^P = \alpha \times \mathcal{V}' \tag{20}$$

[2]We use a linear cost and revenue model in this section. The simulation model in Section 6.2 uses a more realistic nonlinear function that captures economies of scale.

where α is the peering cost factor ($/Mbps).

For example, in the network of Figure 17, the transit and peering costs of player j are given by:

$$C_j^T + C_j^P = P_g \times (V_{jw} + V_{wy}) + \alpha \times (V_{ij} + V_{jx} + V_{iy} + V_{xy}) \tag{21}$$

Similarly, j's revenue is given by:

$$R_j = P_j \times (V_{jy} + V_{wy} + V_{iy} + V_{xy}) \tag{22}$$

In practice, peering is much cheaper than transit, meaning that $\alpha \ll P_v$ for any provider v.

Utility: The peering strategies s_i and s_j determine the interdomain topology of the underlying network (who is peering with whom), and thus the traffic flow on each transit and peering link. These traffic volumes then determine the utility of each player. So, we express the utility of each player p as a function of the peering policies of i and j: $u_p(s_i, s_j)$, $p \in \{i, j\}$. The strategy space of each player consists of the three previous strategies (R, S, O) and is denoted by $\mathcal{S}$.

The utility of player p is its revenue minus its transit and peering costs,

$$u_p(s_i, s_j) = R_p - C_p^T - C_p^P \tag{23}$$

where the revenue and cost terms are calculated as previously described.

Repeated game: Network formation takes place in discrete time ("rounds"), with players i and j playing one after the other. Without loss of generality, the game starts with i's action. The initial condition of the game is the pair of peering strategies (s_i^0, s_j^0) at t=0, which also determines the initial topology. In each round, a player computes its own utility under each of the three candidate peering strategies, and selects the peering strategy that maximizes its utility at that time. In other words, each player acts myopically based on the information that it currently has, without trying to predict the actions of other players in future rounds ("best-response dynamics") and without trying to coordinate with other players.

Specifically, when player p plays at time t, p selects the policy s_p^t that maximizes its own utility, given the policy selection of the other player $(-p)$ in the previous round. Thus, p solves the optimization problem:

$$\max_{s_p^t \in \mathcal{S}} u_p^t(\, s_p^t,\, s_{-p}^{t-1}) \tag{24}$$

We assume that if two strategies give the same utility, the player will choose the strategy that results in the minimum number of peering links (a more manageable configuration in practice). In other words, we break any ties in favor of first the Restrictive and then the Selective strategy.

The game terminates if the network reaches a Nash equilibrium, meaning that none of the two players can increase its utility by unilaterally switching to a different peering strategy. So, the strategy pair (s_p^*, s_{-p}^*) is an equilibrium if

$$u_p(s_p^*, s_{-p}^*) \geq u_p(s_p, s_{-p}^*) \;\; \forall s_p \in \mathcal{S} \tag{25}$$

6.1.2 Stability and Equilibria

The initial strategy vector (s_i^0, s_j^0) can take nine possible values, given that $\mathcal{S}_p = \{R, S, O\}$ and $p \in \{i, j\}$. It is easy to see that the Restrictive strategy is always dominated by the Selective and Open strategies for both i and j. Hence, we do not show the utility under the Restrictive strategy and focus on the remaining four initial strategy vectors. For each such vector we need to consider separately whether w qualifies to be a peer of each provider under the Selective strategy, i.e., whether $I_\sigma(p, w) = 1$ or not for $p \in \{i, j\}$ (four cases). So, overall there are 16 possible cases that need to be analyzed.

We have confirmed that the previous repeated game converges to a Nash equilibrium in all cases. Further, as shown in Section 6.1.3, there are only two possible equilibria: (S, S) and (O, O). In other words, eventually both providers use either the Selective or the Open strategy. It is possible to explain the gravitation towards Open peering through the simple one-shot game equilibria. However, that does not capture all the cases in which the network converges to Open peering.

6.1.3 Best-Response Dynamics

In this section, we analyze the game in detail, focusing on the sequence of peering decisions by each provider, for the most interesting of the previous 16 cases.

6.1.3.1 $(\mathbf{s_i^0}, \mathbf{s_j^0}) = (\mathbf{S}, \mathbf{S}), \mathbf{I}_\sigma(\mathbf{i}, \mathbf{w}) = \mathbf{1}, \mathbf{I}_\sigma(\mathbf{j}, \mathbf{w}) = \mathbf{1}$

We first consider the case that w qualifies to be a peer of i and j under Selective peering. Player i plays first and evaluates all peering strategies. Switching to Open does not increase i's utility because that provider can peer with both w and j under the Selective strategy, and so it can reach everyone (except g) through its peering links. Thus,

$$u_i(S, S) - u_i(O, S) = 0 \tag{26}$$

j carries out the same analysis and also decides to stay with the Selective strategy. So the resulting equilibrium is (S, S).

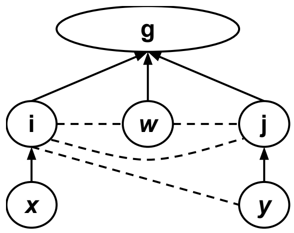
An example of this case is when major content providers such as Google or Facebook (w in the model) have sufficiently large traffic volume to peer with transit providers that use the Selective strategy. Non-tier-1 transit providers (i and j in the model) peer with such content providers, resulting in lower transit costs for both the content provider and the transit provider.

6.1.3.2 $(\mathbf{s_i^0}, \mathbf{s_j^0}) = (\mathbf{S}, \mathbf{S}), \mathbf{I}_\sigma(\mathbf{i}, \mathbf{w}) = \mathbf{0}, \mathbf{I}_\sigma(\mathbf{j}, \mathbf{w}) = \mathbf{1}$

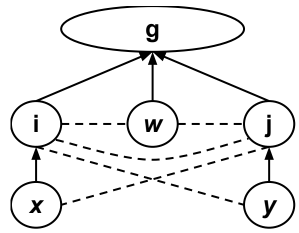
We now consider the case that w does *not* qualify to be a peer of i when $s_i = S$, but it qualifies to be a peer of j when $s_j = S$.[3] In this case, i finds that Open dominates the Selective strategy,

$$u_i(O, S) - u_i(S, S) = (P_g - \alpha) \times (V_{iw} + V_{wx}) \geq 0 \tag{27}$$

[3]The case that $I_\sigma(i, w) = 1$ and $I_\sigma(j, w) = 0$ is symmetric.



(a) Network after i plays



(b) Network after j plays

Figure 18: Network formation in Case-2

because of the reduction in transit costs when the traffic that it exchanges with w is routed through a peering link; recall that $P_g > \alpha$ (transit is more expensive than peering).

Under the Open strategy however, i will also peer with y, the customer of j. The resulting network is shown in Figure 18a. Note that, as a result of the peering link between i and y, provider j now loses the revenue that was due to the traffic $V_{iy} + V_{xy}$; that traffic now bypasses j.

When it is j's turn to play, it also finds that Open dominates Selective,

$$u_j(O,O) - u_j(O,S) = (P_j - \alpha) \times T_{xy} \geq 0 \tag{28}$$

Note that the Open strategy is better for j even though it was able to exchange traffic with i, x and w through peering links even under the Selective strategy. The reason is that if j uses Open peering it can directly peer with x, and so the traffic from x to y, T_{xy}, will be routed again through j, partially alleviating j's earlier loss in revenue. On the other hand, the traffic flow from y to x, T_{yx} still bypasses j through the peering link L_{iy}. Thus, j also adopts the Open strategy, it peers with x, and the new strategy vector becomes (O, O).

When the two players play again, they find that any unilateral deviation from the Open strategy would reduce their utility:

$$\begin{aligned} u_i(O,O) - u_i(S,O) &= (P_i - \alpha) \times T_{yx} \\ &+ (P_g - \alpha) \times (V_{iw} + V_{wx}) \geq 0 \end{aligned} \tag{29}$$

$$u_j(O,O) - u_j(O,S) = (P_j - \alpha) \times T_{xy} \geq 0 \tag{30}$$

Thus, the network reaches the equilibrium (O, O).

The net difference in i's utility between the start of the game and this equilibrium is given by

$$\begin{aligned} u_i(S,S) - u_i(O,O) &= (P_i - \alpha) \times (V_{jx} + T_{xy}) \\ &- (P_g - \alpha) \times (V_{iw} + V_{wx}) \end{aligned} \tag{31}$$

i's utility at equilibrium may be less than its initial utility. When i adopts the Open strategy, it peers not only with w (to reduce its upstream peering costs) but also with j's customers, thereby diverting part of j's customer traffic directly to i. Then, j also adopts Open peering so that it can partially alleviate this loss in transit revenue. In doing so, j diverts part of i's customer traffic directly to j. Hence, while i initially benefits from a reduction in transit costs, it finally also suffers a loss in transit revenue. The net effect on the utility of i and j depends on the relation between the transit prices of the involved providers and the relative size of the affected traffic flows.

Effect of traffic volume: Let us further discuss the role of the traffic that i and its customers exchange with w ($V_{iw} + V_{wx}$ in Equation 31), and the traffic that i's customers exchange with j and its customers ($V_{jx} + T_{xy}$ in Equation 31). The former is traffic for which i saves transit costs by peering with w, while the latter is traffic for which i loses revenue when j adopts Open peering.

As a first-order approximation, we can assume that the transit price of all providers is roughly the same, perhaps due to competition (i.e., $P_i \approx P_j \approx P_g$). Then, according to Equation 31, Selective peering is preferred if $(V_{jx} + T_{xy}) \gg (V_{iw} + V_{wx})$. This situation would arise if x is a much larger content provider than w. i cannot afford to lose the transit revenue from its existing customer x, which is what would happen if both providers use Open peering.

If, however, $(V_{iw} + V_{wx}) \gg (V_{jx} + T_{xy})$, then switching to Open peering is preferred. Such a situation can arise if w is a much larger content provider than i's customers, and so i would incur a large transit cost if not peering with w. Although i's adoption of Open peering forces j to adopt Open peering as well (resulting in a reduction of i's revenue), this revenue loss is much smaller than the upstream transit cost that i would have incurred by not peering with w.

Similar considerations apply to j.

6.1.3.3 $(\mathbf{s_i^0}, \mathbf{s_j^0}) = (\mathbf{S}, \mathbf{S})$, $\mathbf{I}_\sigma(\mathbf{i}, \mathbf{w}) = \mathbf{0}$, $\mathbf{I}_\sigma(\mathbf{j}, \mathbf{w}) = \mathbf{0}$

This case also results in the (O, O) equilibrium. i initially adopts the Open strategy to reduce upstream transit costs. j adopts Open peering to reduce its own upstream transit costs or to recover lost revenue, as explained in Section 6.1.3.2. The analysis of the rest of the game is the same as in Section 6.1.3.2.

6.1.3.4 $(\mathbf{s_i^0}, \mathbf{s_j^0}) = (\mathbf{O}, \mathbf{O})$, $\mathbf{I}_\sigma(\mathbf{i}, \mathbf{w}) = \mathbf{1}$, $\mathbf{I}_\sigma(\mathbf{j}, \mathbf{w}) = \mathbf{1}$

In this case, w qualifies to be a peer of both i and j under Selective peering. However, both players start from the Open strategy. The initial network for this game is shown in Figure 18b. i can avoid any upstream transit cost with the Selective strategy since $I_\sigma(i, w) = 1$. However, if i adopts Selective peering, it would need to depeer y leading to a loss in revenue because of the flow T_{yx}, as shown in Equation 29. Consequently, i stays with the Open strategy. j acts in the same manner. Neither player changes its peering strategy and the equilibrium is (O, O).

The equilibrium (O, O) is suboptimal for both i and j. In the case of i, for instance,

$$u_i(S, S) - u_i(O, O) = P_i \times V_{jx} + (P_i - \alpha) \times T_{xy} \geq 0 \tag{32}$$

Note that the peering constraints on w in this case are the same as in Section 6.1.3.1, but the initial peering strategies are different. While the game of Section 6.1.3.1 reaches the optimal equilibrium (S, S), this game stays at the suboptimal equilibrium (O, O).

6.1.4 Peer Preference or Peer Pressure?

We summarize and generalize the effect that was observed in the previous game as follows: a transit provider may decide to switch to Open peering to reduce its upstream transit costs. By doing so, it can form peering links with at least some customers of its existing peers, diverting revenue-generating traffic from the latter. Those peers would then have the incentive to also switch to Open peering so that they can partially alleviate their lost revenue by attracting traffic that is destined to their customers through direct peering links with others. Thus, transit providers can end up in a state where the loss in transit revenues is larger than their savings in upstream transit costs.

Instead of adopting Open peering to reduce upstream transit costs ("peer preference") some transit providers may be forced to do so to partially alleviate the transit revenue loss caused by their peers ("peer pressure"). We showed that the resulting Open peering equlibrium may be suboptimal for transit providers.

The gravitation of transit providers towards Open peering occurs due to (a) myopic behavior and (b) lack of coordination among peering transit providers. For example, in case 6.1.3.3 i myopically decides to keep the peering link L_{iy}; otherwise the removal of that link would have reduced its utility. Had i switched to Selective peering, accepting a short-term loss, j would find the contentious link L_{jx} redundant and it would also switch to Selective. In other words, players i and j peer with y and x, respectively, not out of preference but because of the pressure to avoid short-term loss.

One could argue that our assumptions of myopic behavior and lack of coordination among Internet transit providers are over-simplistic. It may be true that in a "tiny" Internet with just a handful of providers some form of coordination, or anticipation of the actions of other players, is feasible. Considering however that the Internet consists of thousands of providers, and that each of them only has limited information about the traffic, customers, peers, or even the strategic objectives of other providers, we believe that the previous two assumptions are not unrealistic in practice. In section 6.2, we show with large-scale simulations and under more realistic conditions that the observed gravitation towards Open peering is also evident there.

6.2 Computational Study

The analytical model of the previous section only considers two transit providers and it does not incorporate several factors that are important in practice such as dynamic, location-dependent competitive pricing, economies-of-scale, public vs. private peering, heavily skewed traffic matrix, etc. In this section, we employ computational agent-based modeling involving a large number of agents in a realistic setting to validate and further investigate the analytical results of the previous section. The main objective is to examine whether a move of transit providers towards Open peering can be observed under more realistic conditions. Further, we want to explore which classes of providers are more affected by this move, and to determine the economic impact of Open peering on the AS population in a macro scale.

6.2.1 Computational Model Description

We introduce here two modifications to GENESIS for the purposes of this study:

1. In the original GENESIS model, transit providers are assigned a peering strategy based on their hierarchical status in the network (Tier-1 transit providers use Restrictive, non-Tier1 transit providers use Selective and stubs use Open). In order to reflect the peering strategy decision process described in section 6.1.1, we modify GENESIS so that transit providers evaluate each of the three peering strategies and choose the one that maximizes their utility.

2. In the original GENESIS model, transit prices are randomly assigned to ASes. Further, these randomly assigned prices do not change over the course of the simulation. Here, we introduce competitive, location-dependent dynamic pricing. All

transit providers at a given location have the same price. Thus, a transit provider which has presence in more than one locations may have a different price at different locations. The greater the number of transit providers at a location, the lower the transit price. The parameterization of this pricing model is based on data from TeleGeography [102].

6.2.2 Simulation Results

We begin by comparing the following two *scenarios*: *Selective-Restrictive* (SR) and *Selective-Restrictive-Open* (SRO). Under the *SR* scenario, transit providers choose only between the Selective and Restrictive strategies. In the *SRO* scenario, transit providers choose between Selective, Restrictive and Open. Stubs always use Open peering in both scenarios. In each scenario, we run multiple simulations, each with a distinct population of agents, to generate 100 network equilibria. A comparison of the previous two scenarios allows us to investigate the effect of Open peering on both the providers that adopt it and on the Internet as a whole.

6.2.2.1 Gravitation towards Open peering

In this section, we compare the *SR* and *SRO* scenarios in terms of the peering strategies adopted by the population of transit providers.

The distribution of peering strategies in the *SR* scenario shows that 90% of providers use Selective peering, while the remaining 10% use Restrictive. In *SR*, most providers peer with agents that have similar hierarchical status. The peers of transit providers include large content providers and consumer stubs that are able to satisfy the Selective peering criteria by virtue of their large traffic volume. On the other hand, the *SRO* scenario results in a radical change in the peering strategy distribution – 79% of transit providers adopt Open peering, 20% adopt Selective peering, while only 1% adopt Restrictive.

We find that the attraction towards Open peering is not uniform across all transit providers. Figure 19 shows that the fraction of transit providers adopting Open peering decreases as

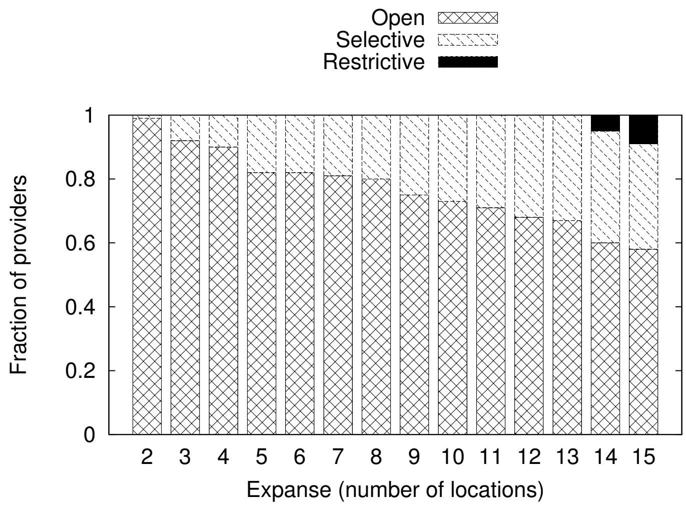


Figure 19: Peering strategy distribution – classification by geographical expanse.

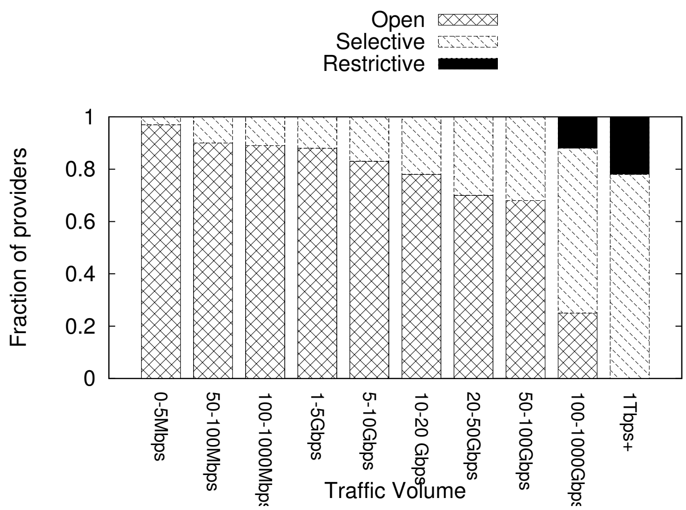


Figure 20: Peering strategy distribution – classification by traffic volume.

their geographical expanse[4] increases. Similarly, Figure 20 shows that the fraction of agents adopting Open peering decreases as their traffic volume increases. When classified based on network hierarchy we find that 6.5% of Tier-1 (agents without transit providers), 58% of Tier-2 (agents which are transit customers of Tier-1 providers) and 87% of Tier-3 (all non-Tier1 and non-Tier2 agents) transit providers adopt Open peering.

What causes these differences in the adoption of Open peering? The geographical

[4]The geographical expanse of a provider is the number of locations in which it is present. Recall that two agents can interconnect only if they are co-located.

expanse and peering strategy of a provider are correlated for two reasons. First, the local traffic of an agent is a function of its geographical expanse; as expanse increases, so does its local traffic volume [74]. Second, an agent with large expanse can attract more customers, which increases its transit volume. A transit provider with large expanse (and hence large traffic volume) is able to peer with other large transit providers using the *Selective* or *Restrictive* policies, avoiding peering with smaller agents.

6.2.2.2 Impact on economic utility

The conventional wisdom is that Open peering is generally associated with a reduction of upstream transit costs and thus, increased utility. However, the complex interdependencies between providers that were discussed in Section-III often cause the opposite effect, i.e., Open peering results in utility loss. In each of the 100 equilibria that we generated using GENESIS, the cumulative utility of all transit providers under the *SRO* scenario is lower than that of the *SR* scenario. As a whole, the population of transit providers does better without Open peering.

A decrease in the cumulative utility of the provider population under *SRO* does not imply, however, that *all* providers see lower utility. We find that 30% of the transit providers have higher utility in the *SRO* scenario. To understand this effect, recall that a provider's utility is a function of its transit costs, peering costs, and transit revenues. We classify transit providers into two classes based on whether their utility increases or decreases by more than 10% between the *SR* and *SRO* scenarios. Providers of both classes see an increase in peering costs and a decrease in transit costs under *SRO*. The difference between the two classes is due to changes in transit revenues. Practically all transit providers that have lower utility under *SRO*, see their transit revenues decrease by more than 20% in that scenario. Among the transit providers that experience a utility increase on the other hand, 70% do not see a significant variation (meaning, it stays within 20% of their utility under *SR*), and only 10% of them have a larger utility increase. Providers that gain significantly in the *SRO*

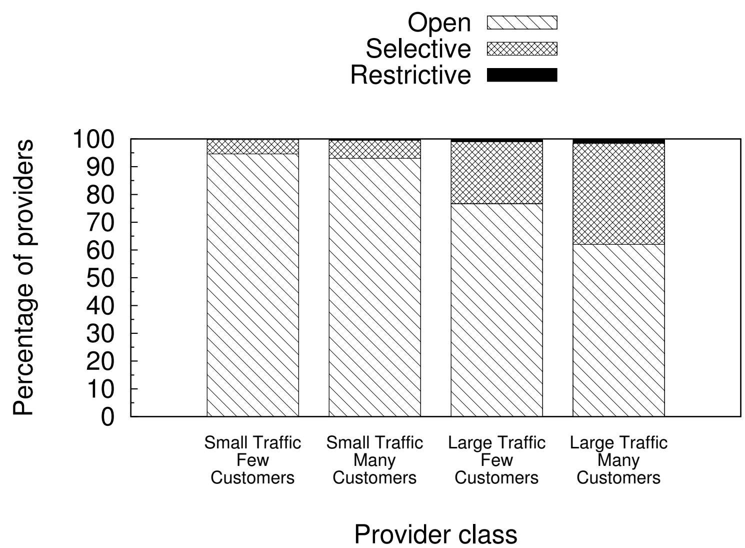


Figure 21: Peering strategy adoption by 4 classes of transit providers.

scenario are typically those that a) have customers who cannot peer with other providers (as a result of co-location constraints) and b) they can peer with many other agents.

6.2.2.3 Who gains and who loses from Open peering?

We examine here in more detail the characteristics of providers that either gain or lose utility as a result of the gravitation towards *Open* peering. To better understand which providers gain or lose from *Open* peering, we classify them into 4 classes, based on their traffic volume and number of customers.

Class-1: Small traffic volume, few customers.

Class-2: Small traffic volume, many customers.

Class-3: Large traffic volume, few customers.

Class-4: Large traffic volume, many customers.

Class-1 includes players in the bottom 30% of providers by traffic volume and the bottom 30% of providers by number of customers. We identify providers in the other three

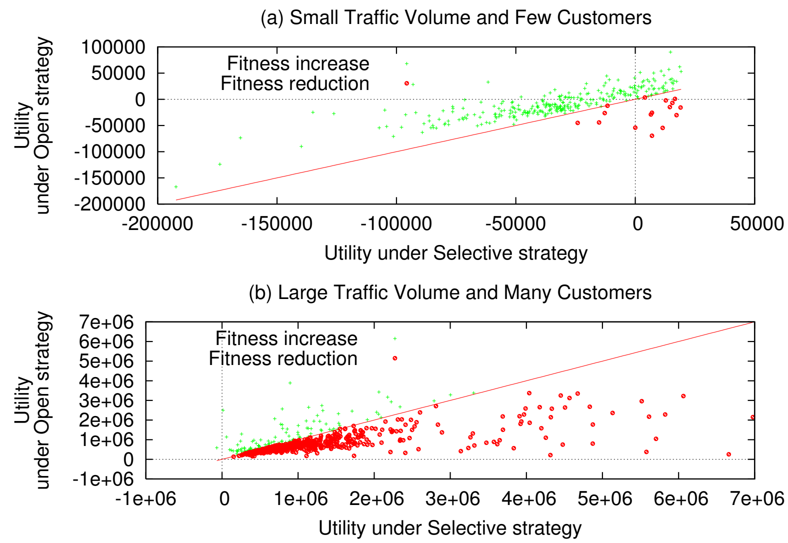


Figure 22: Utility variations in two classes of transit providers.

classes similarly. Based on this classification, 16% of providers are in Class-1, 9% in Class-2, 9% in Class-3 and 37% in Class-4. Figure 21 shows the peering strategy distribution in each class. We find that the affinity for *Open* peering decreases as the traffic volume and number of customers increase. In each class, we identify providers that use *Selective* peering under *SR* and *Open* peering under *SRO*. Figures 22(a) and 22(b) show, respectively, the utility of nodes in Class-1 and Class-4 when they switch from *Selective* under *SR* to *Open* under *SRO*.

Class-1: 90% of Class-1 players undergo an increase in utility. They reduce their upstream transit costs through Open peering as they are denied peering by larger providers due to their small size. Their customers do not have many peers since they are even more limited in geographic expanse. This makes Class-1 player less vulnerable to their transit traffic being diverted away from them.

Class-4: Providers in Class-4 mostly lose by adopting *Open* peering; 84% of them show utility loss. Their large number of customers makes such providers more vulnerable to having their transit traffic being diverted away from them as their customers peer with other providers. Providers in Classes 2 and 3 have less predictable behavior due to their conflicting characteristics. 55% of providers in Class-2 and 25% in Class-3 increase their utility with Open peering.

CHAPTER VII

PROPOSED PEERING STRATEGIES

7.1 A variation of Open peering strategy

The combination of myopic peering strategy selection and lack of coordination between transit providers results in utility loss for many transit providers. The main underlying issue is that, under the Open strategy, providers peer with customers of their peers. Here, we consider a simple coordination scheme in which transit providers agree not to do that. The proposed scheme is referred to as **Direct Customer Forbiddance (DCF)**. With DCF, a provider p can still peer openly but it should not peer with anyone that is a customer of p's peers.

To illustrate this rule, we refer to the network of Figure 17. If i and j adopt the DCF policy, they cannot peer with y and x respectively. In practice, it is feasible for a transit provider i to infer the customers of an existing peer j by examining the BGP routes that j sends to i over the peering session.

7.1.1 Utility under DCF

Consider, for instance, the network of Section 6.1.3.2. If the DCF constraint is adopted, i will switch to Open peering so that it can directly peer with w but i will not peer with y. This allows i to divert all its transit traffic to peering links L_{ij} and L_{iw}. Since, no customer traffic is diverted away from j, the latter does not have any benefit to switch to Open peering and it stays with the Selective strategy. The equilibrium (O, S) in this case is optimal for both players:

$$u_i(O,S) - u_i(O,O) = (P_i - \alpha) \times (V_{jx} + T_{xy}) \geq 0 \quad (33)$$

$$u_j(O,S) - u_j(O,O) = (P_j - \alpha) \times (V_{iy} + T_{yx}) \geq 0 \quad (34)$$

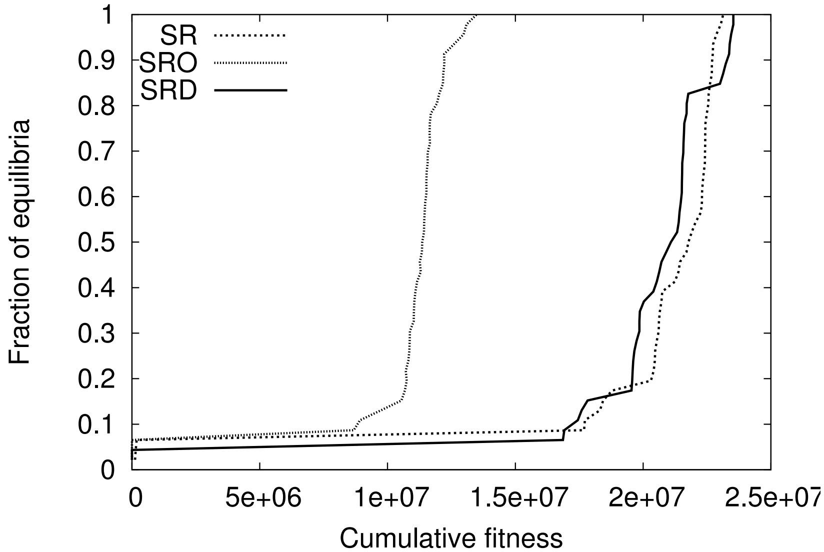


Figure 23: Cumulative utility distribution of transit providers under 3 scenarios

Recall that the network in Section 6.1.3.2 reached equilibrium (O, O) where i not only reduced its upstream transit costs but also suffered a loss in transit revenue. After the introduction of DCF, i only reduces its upstream transit costs. Hence, the DCF variant improves i's utility.

We have also investigated the impact of the DCF Open peering variant on different types of providers using GENESIS. We find that under *SRD*, the cumulative utility of transit providers is greater than under *SRO* and it approaches that with the *SR* scenario. Figure 23 shows the CDF of the cumulative utility of transit providers that use *Selective* peering under the *SR* scenario, but switch to *Open* under *SRO* and *DCF* under *SRD*. The CDF is computed across 100 equilibria.

The cumulative utility of the transit provider population improves with DCF. This is because (a) transit providers no longer "steal" revenue-generating traffic from their peers and (b) transit providers can aggregate peering traffic over few links, reducing peering costs due to the related economies-of-scale. Note, however, that DCF will not have a positive effect on all transit providers. Transit providers higher in the network hierarchy will be more disinclined to peer with those lower in the hierarchy. Hence, some transit

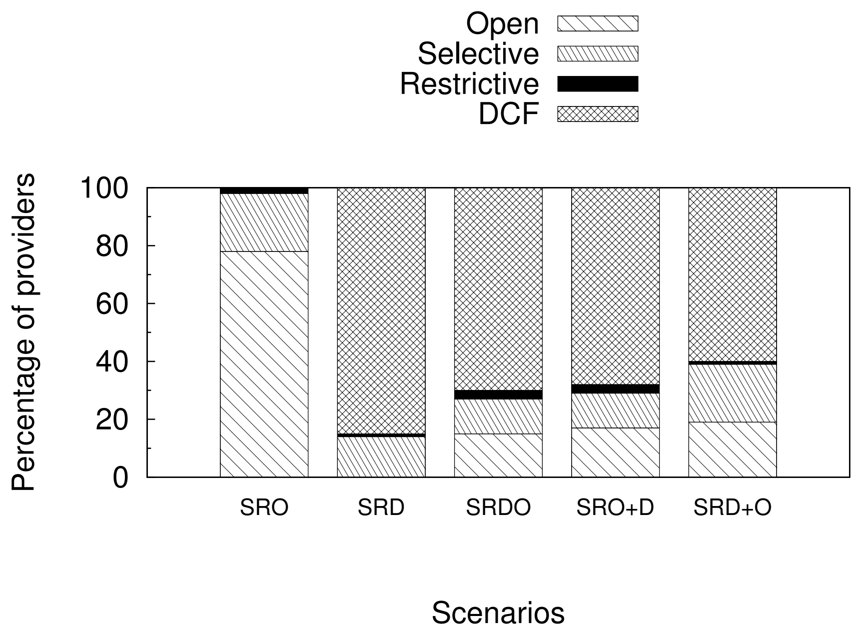


Figure 24: Strategy distribution of providers in five distinct scenarios

providers lower in the hierarchy may have a negative impact on their utility under DCF. In Section 6.2.2.3, we showed that, without DCF, 80% of Class-1 providers gain and 84% of Class-4 providers lose by the introduction of the Open peering strategy. When DCF is adopted, however, 53% of Class-1 providers gain and 68% of Class-4 providers lose utility. In other words, DCF tends to reduce the positive or negative economic impact of Open peering, even though there is still significant variability across different provider classes. Furthermore, if a few providers disregard DCF then their peers conforming to DCF will end up with worse economic utilities.

7.1.2 DCF adoption dynamics

We now explore the behavior of providers if DCF and Open peering are both available as two distinct strategy choices. The key question is whether providers find DCF sufficiently attractive to adopt it without explicit coordination.

We consider the following scenarios:

SRO: Providers choose among: 1) *Selective*, 2) *Restrictive*, 3) *Open*.

SRD: Providers choose among: 1) *Selective*, 2) *Restrictive*, 3) *DCF*.

SRDO: *DCF* and *Open* are both available from the beginning. Providers choose among: 1) *Selective*, 2) Restrictive, 3) Open, 4) *DCF*.

Perturb *SRO* equilibrium with *SRO+D*: When the network reaches equilibrium in the *SRO* scenario, we perturb it by adding the *DCF* strategy in the set of available policies, and force providers to re-evaluate their peering strategy.

Perturb *SRD* equilibrium with *SRD+O*: When the network reaches equilibrium in the *SRD* scenario, we perturb it by adding Open peering to the available strategies, and force all providers to re-evaluate their peering policy.

Figure 24 shows the strategy distribution for each of the previous five scenarios. We find that the providers are more attracted to DCF than to Open. Further, while DCF is able to significantly perturb the *SRO* equilibrium, attracting 68% of the transit providers, the Open policy is not able to significantly perturb the *SRD* equilibrium. These simulation results imply that the adoption of the *DCF* peering variant may be possible, at least between a large subset of transit providers, even if there is no explicit coordination between them.

7.2 Cost-Benefit-Analysis based Peering Strategy

Cost Benefit Analysis: When using Cost Benefit Analysis (CBA) peering strategy, an agent x separately evaluates the impact of each peering link (existing or potential) on its fitness, as opposed to broad rule-based peering strategies, e.g., Selective, Open, etc. For example, under Open strategy, x would peer with all potential peers regardless of the impact of each peering relationship on its fitness. Under CBA, x agrees to establish (or retain) only those peering links that can have a positive impact on its fitness. In GENESIS, only transit providers employ the CBA strategy.

In order to establish a new peering link using CBA, x evaluates each potential peer y by hypothetically establishing a peering link with it. Each new link in the network causes some traffic to be re-routed along different paths based on the interdomain routing policy. x computes the impact of the hypothetical peering link by updating its traffic flow, costs and revenue. x agrees to peer with y if and only if its fitness increases as a result of the hypothetical link. In the real world, such link evaluations are carried out through *peering trials*. Under a peering trial, two ASes establish a peering relationship for a short time period and evaluate the impact of the temporary link on their economic fitness. The link is retained if both peers find the relationship beneficial for their fitness, otherwise it is terminated. Similar evaluations are carried out for existing peers when using CBA. Each existing peer is hypothetically depeered and the impact of depeering on fitness is computed. The link is terminated if depeering improves fitness, otherwise it is retained.

Scalability of CBA: We assume that an agent x can choose any number of peers from $PP(x)$ (from 0 to $n-1$). Traffic in the interdomain network is routed based on the shortest path prefer customer over peer over provider links routing policy. The addition (or removal) of a peering link may affect the flow of traffic on other peering links. Thus, for x, peering with agent y_i may impact the evaluation of agent y_j. We explain this by means of the following example. Let y_j be a customer of y_i. Let V_{xy_i} and V_{xy_j} denote the traffic exchanged between x and y_i and y_j respectively. If x peers with y_i, then traffic from both y_i and y_j flows over the x—y_i peering link as shown in figure 25. The peering cost for x with the single peering link is given by equation 35. If x peers with both y_i and y_j then traffic from both ASes traverses separate peering links as shown in figure 26. The peering cost for x with both peering links is given by equation 36 while equation 37 shows that the cost under the two scenarios is different.

$$PC(x) = \alpha \times (V_{xy_i} + V_{xy_j})^{\beta} \tag{35}$$

$$PC(x) = \alpha \times (V_{xy_i}^{\beta} + V_{xy_j}^{\beta}) \tag{36}$$

$$\because (V_{xy_i} + V_{xy_j})^{\beta} < V_{xy_i}^{\beta} + V_{xy_j}^{\beta} \tag{37}$$

Hence the question is: how should x go about finding its peers from among potential peers? In order to find the optimal set of peers, x would have to evaluate each combination of peers. The number of such combinations is given by:

$$\sum_{k=1}^{n} \binom{n}{k} \tag{38}$$

Note that each combination would involve evaluation of k peering links by both agents involved. Given the large co-location density in many regions of the interdomain network, the number of evaluations required to determine the optimal set of peers may be infeasible.

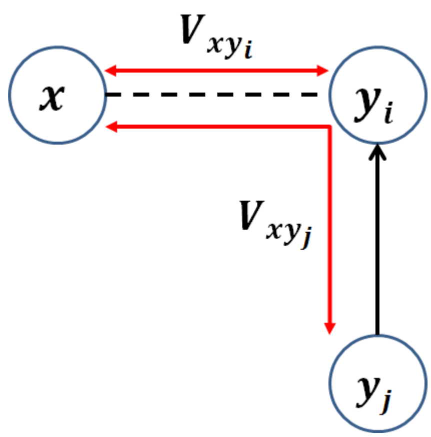


Figure 25: Peering between x and y_i only

CBA heuristic: CBA involves computation of all traffic flows, costs and revenue by x. Hence, employing this strategy to evaluate all potential and existing peers is not scalable. We propose a simple heuristic to alleviate scalability issues with CBA. Although our proposed heuristic does not compute the optimal set of peers, yet it allows agents to prioritize peers based on peering traffic aggregation and avoid redundant evaluations.

Our heuristic exploits a key feature of the *valley-free* routing policy employed in the Internet. It is based on the notion that if an AS x can reach AS y through an existing

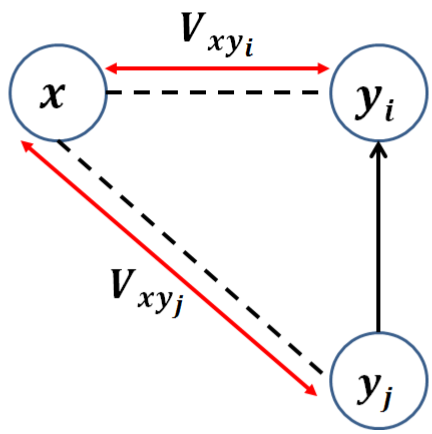


Figure 26: Peering between x and y_i, and x and y_j

peering link L_{xz} with another AS z, then the peering link L_{xy} would be redundant. Such a link would not save x any transit costs and would only add to its peering costs. Thus, if x finds that it has a peering path to y, it can refuse to peer with y without actually evaluating it. Note that if x is able to reach y through an existing peering link, then it implies that y is in the customer tree of an existing peer of x.

This heuristic is explained in Figure 27. The figure shows x and z as peers while y is in the customer tree of z. In Figure 27a, x is not a peer of y. In this network, traffic from x to y flows over the peering link L_{xz}. Thus, x is able to reach y over an existing peering link. If V_{xz} and V_{xy} is the total traffic volume exchanged between x and z, and x and y respectively, then the peering cost of x is given by:

$$PC(x) = \alpha \times (V_{xz} + V_{xy})^{\beta} \tag{39}$$

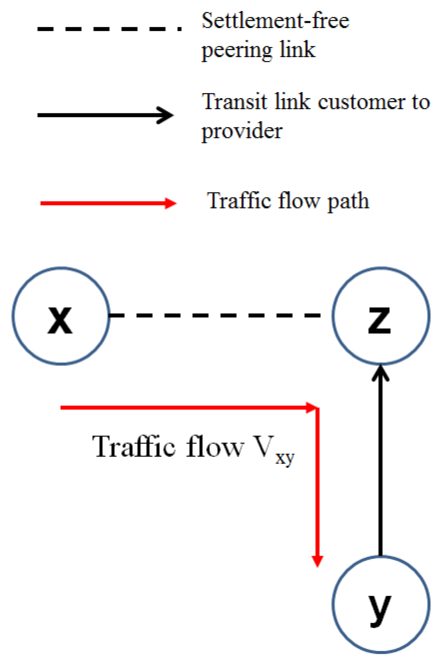
In Figure 27b, x peers with z. Thus, traffic between x and z flows over the direct peering link and now the peering cost of x is given by:

$$PC'(x) = \alpha \times (V_{xz})^{\beta} + \alpha \times (V_{xy})^{\beta} \tag{40}$$

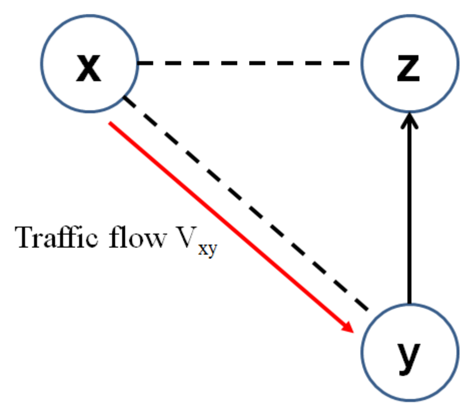
Note that the peering cost of x is increased because of the additional peering link.

$$PC(x) < PC'(x) \because (V_{xz} + V_{xy})^{\beta} < (V_{xz})^{\beta} + (V_{xy})^{\beta} \tag{41}$$

Thus, if an agent x can reach another agent y through an existing peer higher up in the network hierarchy, it does not need to establish a redundant peering link with y. The redundant peering link does not reduce upstream transit costs; on the other hand it adds to the cost of peering by reducing the advantage of economies-of-scale. Therefore, x can decide not to peer with y without actually doing cost-benefit-analysis. Algorithms 1 and 2 give the procedures for depeering and peering respectively using CBA.



(a) y in customer tree of x



(b) x peering with y

Figure 27: CBA heuristic example

Input $PP(i) = \{x_1, x_2, ..., x_n\}$

Sort $PP(i)$ hierarchically $PP(i) = \{x_1, x_2, ...x_t, x_{t+1}, ...x_z\} : x_t \notin C(x_{t+1})$

Do $PP(i) \leftarrow PP(i) - x_k \, : \, x_k \in C(x_j), \, j < k$ {Remove from $PP(i)$ all peers which are in customer trees of other existing peers}

Do CBA for $\forall x_j \in PP(i)$

> **Do** $F_{original} \leftarrow F(i)$
>
> **Do** Remove peering link between i and x_j
>
> **Do** Route traffic
>
> **Do** Compute $F(i)$
>
> $F_{update} \leftarrow F(i)$
>
> **If** $F_{update} > F_{original}$
>
> **Do** $PP(i) \leftarrow PP(i) - x_j$

Algorithm 1: Depeering by agent i using CBA

Do $PP'(i) \leftarrow j \ \forall j \notin C(k) \ \forall k \in PP(i)$

Do $PP'(i) = PP'_P(i) \bigcup PP'_S(i) : C(j) = \emptyset \ \forall j \in PP'_P(i),\ C(j) \neq \emptyset \ \forall j \in PP'_P(i),\ PP_P(i) \bigcap PP'_S(i) = \emptyset$

Sort $PP'_P(i)$ hierarchically $PP'_P(i) = \{x_1, x_2, ...x_t, x_{t+1}, ...x_z\} :\ x_t \notin C(x_{t+1})$

Do CBA $\forall x_j \in PP'_P(i)$

Do $F_{original} \leftarrow F(i)$

Do Establish peering link between i and x_j

Do Route traffic

Do Compute $F(i)$

$F_{update} \leftarrow F(i)$

If $F_{update} > F_{original}$

Do $PP(i) \leftarrow PP(i) + x_j$

Do $PP_S(i) \leftarrow PP_S(i) - x_k \ \forall x_k \in C(x_j),\ x_k \in PP_P(i)$

Do CBA $\forall x_j \in PP'_S(i)$

Do $F_{original} \leftarrow F(i)$

Do Establish peering link between i and x_j

Do Route traffic

Do Compute $F(i)$

$F_{update} \leftarrow F(i)$

If $F_{update} > F_{original}$

Do $PP(i) \leftarrow PP(i) + x_j$

Algorithm 2: Peering by agent i using CBA

CHAPTER VIII

CONCLUSIONS & FUTURE WORK

The Internet consists of thousands of heterogeneous Autonomous Systems (ASes) that voluntarily form bilateral (sometimes conditional) interconnection agreements to provide end-to-end reachability. This thesis on a specific class of links - peering, from an economic perspective. Peering interactions between ASes in the Internet are local, without centralized control or regulation, but they often have global impact on the performance and profitability of networks and sometimes the global economy. Additionally, the Internet behaves as a co-evolutionary network in which the state of the nodes and the network topology change at the same time, through coupled interactions.

The main contributions of this thesis include:

1. Identification of fundamental complexities underlying the evaluation of peers and formation of stable peering links in the interdomain network. We identify the topological structure and routing policies in the Internet as key limiting factors in the formation of optimal peering relationships.

2. An empirical study of the state of the peering ecosystem from August 2010 to August 2013. We find strong correlations among different measures of AS size, e.g., advertised address space (from BGP), traffic volume, geographic expanse, etc., and between these size measures and the peering strategies that those ASes use.

3. Development of a large-scale agent-based computational model to study the formation and evolution of the Internet interdomain network.

4. Proposition of a plausible explanation for the gravitation of Internet transit providers towards Open peering and a prediction of its future consequences. Our studies show

that large-scale adoption of Open peering by transit providers can be attributed to their myopic and selfish peering actions and these practices are detrimental to their long-term economic fitness as well.

5. Proposition of two new practical peering strategies. We propose a variant of the contemporary Open peering policy and a new policy based on cost-benefit analysis to replace the contemporary simplistic policies.

Future Work

We identify three main threads for future research in the context of this thesis: (a) optimal connectivity decisions in the Internet interdomain network (b) analysis of the interdomain network topology to ensure traffic routing over trusted ASes and (c) resolution of peering disputes between ASes before they escalate to disconnectivity.

Optimal connectivity decisions in the Internet interdomain network: In this research we will focus on developing algorithms which exploit real-world topology and traffic data to determine an AS' connectivity to optimize its financial utility subject to performance and resource constraints. Current operational practices for connectivity decisions adopt very simplistic and myopic approaches because of the intractability of the problem. However, knowledge of real-world topology, routing policies and some knowledge of traffic matrix can be exploited to significantly reduce the complexity and improve an AS' financial utility.

Peering to ensure traffic routing over trusted ASes: Security and privacy have been the focus of recent debates on the future of the Internet. An AS typically has multiple options (including multiple transit providers and peers) to send traffic to other destinations. Since next-hop neighbors of an AS (both peers and transit providers) also have similar configurations, it results in a wide array of choices for end-to-end paths. So far, topology decisions such as the choice of upstream transit providers and settlement-free peers has been driven by financial and performance considerations only. However, many large ASes are increasingly concerned about the complete path, beyond the next-hop, because of threats to security and privacy of their traffic. For example, an intermediate AS in the path can measure the traffic volume being sent from the source to the destination and can use this information to develop competitive peering strategies. In this research, we intend to propose practical mechanisms whereby an AS can exploit publicly available topology and NetFlow data, utilize simple network tools and a few peering trials to determine its peers so as to ensure that its traffic flows over trusted ASes as much as possible.

Resolution of peering disputes: The third research question in the context of computer networks focuses on Internet peering disputes, which often cause performance and unreachability problems for millions of Internet users. The importance of this question can be judged from the fact that such disputes have increasingly hit the headlines recently, e.g., the Comcast vs. Level-3 peering dispute [94]. Such disputes have led to litigation, calls for intervention by regulators [69] and legislation at the highest levels of government [89]. Moreover, such disputes have sometimes resulted in the partitioning of the Internet rendering significant organizations with critical communication needs, e.g., NASA and Federal Aviation Administration (USA), disconnected from the Internet [103]. Furthermore, the frequency of such disputes is likely to increase in future [96]. In this research we will explore the following question: *what is the fundamental reason behind these disputes and how can they be avoided?* We will analyze such conflicts and propose new paid-peering and pricing schemes to avoid such disputes.

Refined Peering Decisions:

The current economic framework for peering requires that peers negotiate their links based on the aggregate traffic, in both directions, that they exchange between each other. Large ASes often use the ratio of inbound to outbound traffic on a peering link as part of their *selective* criteria to choose peers. The peering ratios model assumes that all traffic is equal in terms of costs and value and therefore traffic volume can be used as a proxy to measure the relative benefit. We believe that traffic ratios are not the most appropriate factor to make peering decisions because the previously mentioned assumptions do not hold true in all cases. The cost of carrying traffic and the value derived from it may be very different across ASes. Hence, peering ratios based decision making should be replaced by more refined cost-benefit-analysis models. We propose that future economic frameworks should enable any two ASes in the Internet to negotiate a price for any traffic flow between a unique source and destination pair. For example AS x should be able to figure out what price it should offer to AS y to reach AS z for a traffic flow associated with service f. Thus, future economic frameworks should enable the peers to put a price/cost tag on each $(source, destination, flow)$ triple. For such a framework, x would need to know (or estimate) the traffic volume to be sent from y to z, the fraction of y's traffic going to z, other options available to y, its own capacity, constraints for the flow f, etc.

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